User Modeling and User-Adapted Interaction (2024) 34:489–547
https://doi.org/10.1007/s11257-023-09380-z

An overview of consensus models for group decision-making and group recommender systems

Thi Ngoc Trang Tran[1,2] · **Alexander Felfernig**[1] · **Viet Man Le**[1,3]

Received: 30 September 2022 / Accepted in revised form: 9 August 2023 / Published online: 22 September 2023

Abstract
Group decision-making processes can be supported by group recommender systems that help groups of users obtain satisfying decision outcomes. These systems integrate a consensus-achieving process, allowing group members to discuss with each other on the potential items, adapt their opinions accordingly, and achieve an agreement on a selected item. Such a process, therefore, helps to generate group recommendations with a high satisfaction level of group members. Our article provides a rigorous review of the existing consensus approaches to group decision-making. These approaches are classified depending on the applied consensus models such as *reference domain* where a set of group members or items is selected for calculating consensus measures, *coincidence method* that calculates the consensus degree between group members depending on the coincidence concept, *operators* that aggregate user preferences, *guidance measures* where the consensus-achieving process is guided by different consensus measures, and *recommendation generation* and *individual centrality* that enhance the role of a moderator or a leader in the consensus-achieving process. Further consensus techniques for group decision-making in heterogeneous and large-scale groups are also discussed in this article. Besides, to provide an overall landscape of consensus approaches, we also discuss new consensus models in group recommender systems. These models attempt to improve basic aggregation strategies, further consider social relationship interactions, and provide group members with intuitive descriptions regarding the cur-

✉ Thi Ngoc Trang Tran
ttrang@ist.tugraz.at; ttntrang@hueuni.edu.vn

Alexander Felfernig
alexander.felfernig@ist.tugraz.at

Viet Man Le
vietman.le@ist.tugraz.at; lvman@hce.edu.vn

1 Institute of Software Technology, Graz University of Technology, Inffeldgasse 16b/II, 8010 Graz, Styria, Austria

2 School of Hospitality and Tourism, Hue University, Hue, Vietnam

3 University of Economics, Hue University, Hue, Vietnam

rent consensus state of the group. Finally, we point out challenges and discuss open topics for future work.

Keywords Group recommender systems · Group decision-making · Consensus-achieving processes · Consensus models · Negotiation models

1 Introduction

Making a decision is one of the most usual human activities in daily life. There is an increasing need for group decision-making processes where a group of users jointly decides on a common solution for a problem consisting of many potential items. For instance, in requirements engineering scenarios, stakeholders in a software development team have to jointly select one/some requirement(s) from a set of potential requirements to be implemented in the next release (Ninaus et al. 2014).

Group recommender systems have emerged as an effective tool that suggests interesting, suitable, and valuable items that are consumed socially by groups of users (Pérez-Almaguer et al. 2021). These systems can also support group decision-making processes, where group members are allowed to first articulate their preferences for items and thereafter perform a recommendation process to suggest the most appropriate item(s) for the group (Castro et al. 2018; Nguyen and Ricci 2018; Yera et al. 2018). A group recommendation can be generated by one of the following approaches: *aggregated predictions* and *aggregated models* (Felfernig et al. 2018a; Masthoff 2015). In the first approach, recommendations are produced for individual group members and then aggregated into a group recommendation. In the second approach, the preferences of individual group members are aggregated into a group model, which is then used to produce a group recommendation. In traditional group recommender systems, an aggregation can be guided by *aggregation strategies*, such as *average, majority, most pleasure,* and *least misery* (Masthoff 2011). However, these strategies do not always generate group recommendations with a high agreement of all group members (Palomeres et al. 2011). There could exist a situation where some group members are dissatisfied with the chosen solution. In this context, it is essential to integrate a *consensus-achieving process* that pursues group members' consensus about the problem before proposing a final decision and thus yields a highly satisfying solution for the group (Palomares et al. 2014a).

The notion of *"consensus"* in consensus-achieving processes can be interpreted in different ways, ranging from *strict consensus* to *soft consensus*. *Strict consensus* is referred to as *complete agreement* that requires a mutual agreement of all group members in all items. This consensus type might be hard or even impossible to achieve, especially in large and diversified groups. In this context, more feasible approaches, so-called *soft consensus*, have been proposed to soften the strict view of the unanimity consensus. Soft consensus can be achieved when most group members participating in a problem agree with the most important items. These soft consensus approaches consider different degrees of partial agreement among group members to decide if a consensus exists and to indicate how far away the group is from ideal consensus.

Most existing studies focus on approaches based on *soft consensus measures* since it is more appropriate for reflecting human perceptions of the consensus concept (Cabrerizo et al. 2017b). Although these approaches have been prominently studied, they are pretty fragmented. Hence, it is crucial to review and summarize the existing research to provide a systematic overview of studies on this topic, focusing on the classification of consensus-based models. To the best of our knowledge, only one related overview paper (Cabrerizo et al. 2017b) exists in the literature. However, this work has two drawbacks: (1) only studies up to 2016 are reviewed and (2) consensus approaches are not discussed in the group recommendation context. In this article, we provide a more complete review of consensus approaches, including *80* related studies, in which there are *53* papers/articles published from 2017 on. Besides, different from the mentioned related work, we present further consensus models integrated into group recommender systems. The contributions of the article are three-fold:

- We discuss widely used approaches to soft consensus models for group decision-making that have been developed based on different methods such as reference domain, coincidence method, OWA operators that aggregate user preferences associated with the support of multiple criteria, guidance measures, recommendation generation, and individual centrality. Besides, we also present further consensus approaches developed especially for heterogeneous and large-scale groups.
- We discuss approaches applied to consensus-based group recommender systems. These approaches propose consensus models for improving basic aggregation strategies, considering group members' social interactions, and intuitively representing the current agreement status of a group. These approaches help to increase group members' mutual awareness w.r.t item preferences, which is the basis for group members' preference adaptations and a highly accepted group recommendation after all.
- We point out challenges and discuss open issues for future work.

The remainder of the article is structured as follows: In Sect. 2, we present the research methodology used as a basis for our article. Section 3 summarizes the basic concepts of group recommender systems, group decision-making, and consensus-achieving processes. Consensus models for group decision-making are discussed in Sect. 4, and further consensus approaches for group recommender systems are presented in Sect. 5. Finally, in Sect. 6, we conclude the article and raise open issues to be addressed in future work.

2 Research methodology

The basis of our analysis was a systematic bibliographic review of the existing literature on consensus models in group decision-making and group recommender systems (Stark et al. 2019; Pincay et al. 2019). We collected relevant references using keywords such as *"group decision-making", "group recommender systems", "group recommendations", "consensus decision-making", "consensus-achieving process"*, and *"negotiation methods"*. To have a deeper look at the consensus approaches in group decision-making, we used additional keywords such as *"soft consensus mod-*

els", "consensus measures", "fuzzy sets", "fuzzy logic", "fuzzy linguistics modeling", "fuzzy preference relation", "consensus degree", and *"linguistic quantifier"*. In order to search for consensus models supported in group recommender systems, the following keywords were used: *"consensus-driven group recommender systems", "social influence", "recommendation performance", "consensus explanations", "information visualization"*, and *"aggregation strategies"*.

We looked for the existing publications in digital libraries such as ACM,[1] Google Scholar,[2] ResearchGate,[3] Science Direct,[4] Scopus,[5] and Springer.[6] To ensure high-quality references, we first checked the title, abstract, keywords, conclusion, tables, and figures of the collected publications. Thereafter, we used the following filtering criteria: *(i)* conference/workshop proceedings, articles, and books/book chapters published by prestigious conferences/workshops, journals, and publishers; *(ii)* presenting detailed discussions on our research topic; and *(iii)* providing logical and reasonable findings related to the research topic. We excluded irrelevant publications that did not meet the filtering criteria.

Based on the mentioned criteria, we identified *170* publications. Thereof, *115* articles have been published in various journals, in which *31 articles* have been published in high-quality journals, such as IEEE Transactions on Fuzzy Systems, IEEE Transactions on Systems, Man, and Cybernetics, Information Fusion, and Knowledge-based Systems. The remaining articles were found in other computer science journals, such as Fuzzy Sets and Systems, Information Sciences, Decision Support Systems, Applied Soft Computing, Informatica, and Expert Systems with Applications. In addition, we collected *44 conference/workshop papers*, in which some of them have been published in prestigious conferences such as ACM Conference on Recommender Systems—*RecSys*, ACM Conference on User Modeling, Adaptation and Personalization—*UMAP*, and ACM Conference on Intelligent User Interfaces—*IUI*. Finally, we filtered out *11 books/book chapters* from well-known publishers such as *Springer, Food Not Bombs, RWS Publications, Harper Collins*, and *Morgan Kaufmann*, which have been regarded as suitable for our study. More details about the distribution of the references according to the mentioned types are depicted in Fig. 1.

1 https://dl.acm.org/.

2 https://scholar.google.at/.

3 https://www.researchgate.net/.

4 https://www.sciencedirect.com/.

5 https://www.scopus.com/home.uri.

6 https://link.springer.com/.

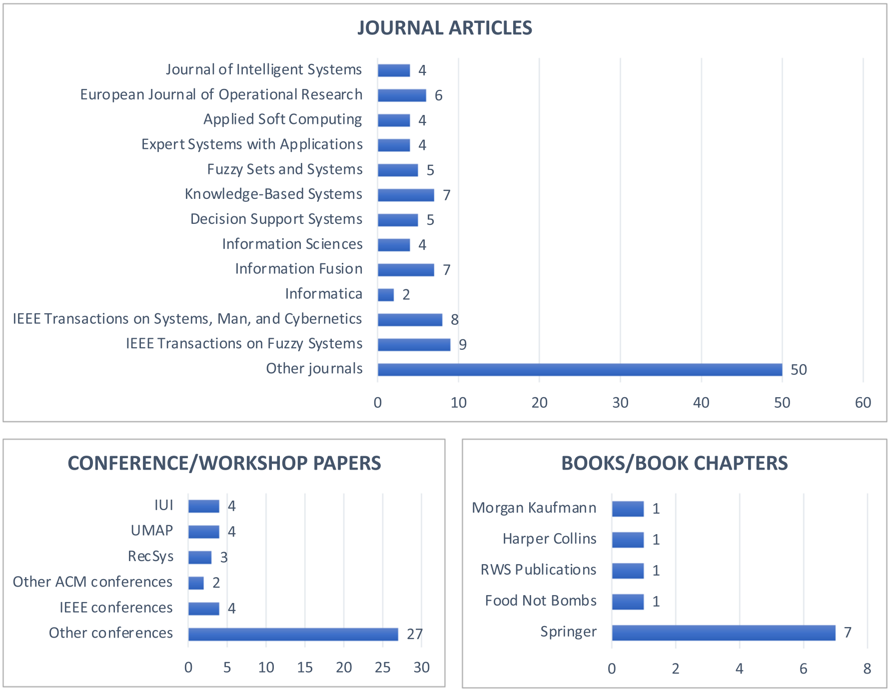


Fig. 1 The distribution of the references according to three types of publications—journal articles, conference/workshop papers, and books/book chapters

3 Fundamental concepts

This section provides a brief overview of group recommender systems, group decision-making, and consensus-achieving processes, which is the basis for further discussions in the follow-up sections.

3.1 Group recommender systems

Recommender systems have been recognized as an effective tool that helps users overcome information overload by selecting valuable information from a vast amount of available data sources (Kapoor 2017). While previously published studies on recommender systems are limited to single-user decisions (Masthoff 2011; Kapcak et al. 2018), there exist plenty of scenarios in reality where decisions are more likely made by groups of users. Some examples thereof are selecting a restaurant to have dinner with family members (Tran et al. 2018) or deciding on a tourism destination for the summer vacation (Ardissono et al. 2003; Tran et al. 2018). *Group recommender systems* have also emerged as an effective tool suggesting interesting, suitable, and valuable items that are consumed socially by groups of users (Pérez-Almaguer et al. 2021). Besides, group recommender systems can also be a powerful tool that supports group decision-making processes. The primary purpose of these systems is to generate recommendations that satisfy the preferences of individual group members as much as possible. One critical task of a group recommender system is to merge the profiles or predictions created for individual group members to achieve a consensus group recommendation (Salamó et al. 2012). In this regard, a group recommendation can be generated in the following steps (Jameson and Smyth 2007):

– *Step 1* (Preference acquisition): The system acquires the preferences of group members for items. Group members' preferences can be collected *explicitly* or *implicitly*. Explicitly, the system collects the preferences of group members for given items by asking them to specify their preferences using, for instance, a five-level rating scale (1—the worst and 5—the best) (Jameson 2004; Nguyen and Ricci 2017a; O'Connor 2001; Samer et al. 2020). Implicitly, group members' preferences can be inferred according to their actions and feedback. For instance, LET'S BROWSE (Lieberman et al. 1998) learns the interest of group members by analyzing the words occurring in the web pages visited by the group. FLYTRAP (Crossen et al. 2002) learns the music preferences of the potential users by noticing what MP3 files they usually play on their computer. Nguyen and Ricci (2018) propose an approach that induces the preference of group members by combining long-term and group-induced preferences. DEEPGROUP (Ghaemmaghami and Abari 2021) uses *reverse social choice* to infer the preferences of a user involved in observed group decisions.
– *Step 2* (Recommendation generation): A group recommendation can be generated by one of the following popular strategies: *aggregated predictions* and *aggregated models* (Felfernig et al. 2018a). *Aggregated predictions* first generate recommendations for individual group members and then propose group recommendations based on merging these recommendations. *Aggregated models* combine all individual group members' preferences into a group preference model (i.e., group profile) that represents the inferred preferences of the whole group. The group profile is then applied to generate group recommendations (Felfernig et al. 2018a). *Aggregated models* are usually helpful when group members want to perform additional actions in the group decision-making process, such as analyzing, negotiating, or adapting the preferences of the group (Jameson and Smyth 2007). Furthermore, these models help to conserve group members' privacy since individual group members' profiles are not recorded in the system (Felfernig et al. 2018a).
– *Step 3* (Recommendation presentation and explanation): A group recommender system should present a recommendation to group members as soon as it has been generated. Since there are many ways to create a group recommendation, it is natural that group members should be aware of how a specific item has been chosen for them (Jameson and Smyth 2007). This is particularly evident since convincing group members that a particular recommendation is suitable for them is especially important (Salamó et al. 2012). There exist different ways to present and explain group recommendations. POLYLENS (O'Connor 2001) shows the predicted rating for each group member and the group as a whole. This system also lets the group know how group recommendations are generated via the *least misery* strategy (Felfernig et al. 2018a) by comparing the predictions for the individual group members with the predictions for the group. Tran et al. (2019) propose

different textual explanation types based on social-choice strategies (Masthoff 2011) to explain group recommendations and increase fairness and consensus perception of group members. Najafian (2020) proposes an approach to generate natural language explanations of group recommendations, taking into account two different aspects: (1) *repairing* that describes a scenario where group members have conflicts and (2) *reassuring* that describes a scenario where all group members agree on the recommended item.

– *Step 4* (Consensus negotiation): Generating a group recommendation is not a one-shot process, but rather a *multifaceted process* since group members' preferences often adapt to other members. It may turn out that what they select for a group does not fully match individual group members' preferences (Nguyen 2017). Moreover, creating a group recommendation based on aggregated strategies could not guarantee a satisfactory outcome for individual group members. In the worst case, it could even trigger opponents among group members (Masthoff 2015). In this context, a *consensus-negotiation process* should be supported to assist group members in achieving a consensus about which recommendation to accept. It is usually assumed that an individual group member will decide whether to accept a recommendation. Let's Browse (Lieberman et al. 1998) adopts this assumption to allow one particular group member to be responsible for the final decision. This group member typically controls the system interaction with other members who play the role of viewers rather than actors (Salamó et al. 2012). However, this approach does not work effectively since, in many other scenarios, final decisions are expected to be made through a group discussion where an extensive debate or negotiation is required. The system at that time should be able to facilitate the necessary communication among group members and help to increase the satisfaction of all group members regarding the final decision.

To better support group discussions of individual group members, *conversational group recommender systems* (Nguyen 2017; Contreras et al. 2021; Emamgholizadeh 2022; Omar et al. 2016) can be developed. The main focus of these systems is to enhance group members' interactions that better support a full decision-making process, including the entire preference elicitation and recommendation phases. Contreras et al. (2021) propose a collaborative model based on social interactions taking place in a web-based conversational group recommender system. This model implicitly infers different roles within a group, namely collaborative and leader user(s). Moreover, it serves as the basis of collaboration-based consensus strategies that integrate individual and social interactions in the group recommendation process. Omar et al. (2016) introduce an approach considering social interactions during the formulation, discussion, and negotiation of the items jointly selected by group members. The system supports a collaborative preference elicitation and a negotiation process where desired items can be defined individually. Besides, a group consensus mechanism is supported, making group members more active in the item filtering process. Further details of how social interactions are taken into account in consensus-based group recommender systems will be discussed in Sect. 5.2.

3.2 Group decision-making

Group decision-making is an everyday activity performed in organizations nowadays. Therefore, related group decision-making problems are required to guarantee proper development in an organization (Palomeres et al. 2011). These problems can be defined as situations where group members have to jointly select a solution from a set of potential items.

There are different *functional perspectives* on which the group decision-making process is done, such as *problem analysis, goal setting, item identification,* and *item evaluation and selection* (Gouran and Hirokawa 1996). *Problem analysis* allows a group to look at the likely causes of the problem and figure out the real problems or the symptoms of the problems. *Goal setting* allows a group to identify the solution to a group decision-making problem. *Item identification* helps a group find possible solutions and involve brainstorming with the entire group. Finally, *item evaluation and selection* allows group members to evaluate the items and pick the best one. This article focuses on the last perspective, where group members utilize a preference structure to express their opinions over a list of potential items. Thereafter, the selection process with two phases is done to reach a final solution for a group decision-making problem. The first phase proceeds with the aggregation of the preferences of group members using aggregation strategies (Felfernig et al. 2018a). In the second phase—*exploitation*, a selection criterion (Herrera et al. 1995; Orlovsky 1978) is adopted to obtain an item or a subset of items as the final solution.

Formally, a group decision-making problem consists of the following main elements (Gallardo et al. 2015; Palomeres et al. 2011):

- A set U of n users (group members) ($U = \{u_1, \ldots, u_n\}, n \geq 2$) who articulate their preferences for a set of items.
- A set X of m items ($X = \{x_1, \ldots, x_m\}, m \geq 2$) to be chosen as potential solutions to the group decision-making problem.
- A set P of users' preferences over the items to describe the opinion of users about items. The preference values are in a rating domain $D (P \subseteq U \times X \rightarrow D)$.

A user's preference for an item can be represented by a *preference structure*. Different preference structures have been used in group decision-making approaches, such as *preference orderings, utility values,* and *preference relations* (Cabrerizo et al. 2017b; Herrera-Viedma et al. 2002; Palomeres et al. 2011):

- *Preference ordering:* A user u_i specifies his/her preferences for a set of m items as an individual preference ordering $O^i = \{o_1^i, \ldots, o_m^i\}$, where $o^i(.)$ is a permutation function over the indexes set $\{1, \ldots, m\}$ (Tanino 1984). A user gives an ordered vector of item preferences from the best to the worst. In the recommendation context, this preference structure can be defined as *"an ordering relation between two or more items to characterize which, among a set of possible choices, is the one that best fits user tastes"* (Brafman and Domshlak 2009; Huang et al. 2015).
- *Utility values*: A user u_i gives his/her preferences on a set of items X by means of a set of m utility values $U^i = \{u_1^i, \ldots, u_m^i\}$, where $u_j^i \in [0, 1]$. The basic idea is that the higher the utility value of an item, the higher the preferences of the user concerning the item objectives (Herrera-Viedma et al. 2002). This preference

structure has been used in *utility-based recommender systems* where suggestions are generated based on the computation of the utility of each item for the user (Huang 2011). Some utility-elicitation methods have been developed based on *Multi-Attribute Utility Theory (MAUT)* (Sarin 2013) to represent a decision maker's complete preference.

- *Preference relations*: The preferences specified by a user u_i are described by a function $\mu_P i : X \times X \rightarrow D$ where $\mu_P i(x_j, x_k) = p^i_{jk}$ can be interpreted as the preference degree or intensity of the item x_j over item x_k expressed in the information representation domain D. This preference structure indicates the concept of *pairwise preferences* in recommendation scenarios when a user does not rate for items separately but instead provides his/her preferences by expressing which item is preferred in a *pair(x_j, x_k)*. Pairwise preferences are naturally expressed by users in many real-life decision-making scenarios. For instance, when selecting a pair of shoes, we do not rate different pairs of shoes separately. Instead, we are more likely to compare them and then select the preferred one (Kalloori et al. 2018).

  Different-types of preference relations can also be used according to the domain where the intensity of the preference is evaluated. Among these types, *fuzzy preference relations* are the most common approach due to their effectiveness in modeling decision-making processes. According to this approach, if $D \in [0, 1]$, every value p^i_{jk} in the matrix P^i represents the preference degree (associated with user u_i) for item x_j over item x_k (normally, it is assumed that $p^i_{jk} + p^i_{kj} = 1, \forall j, k$):

  - $p^i_{jk} = 1/2$ indicates that there are no differences in the preferences of user u_i for items x_j and x_k.
  - $p^i_{jk} = 1$ indicates that the item x_j is absolutely preferred over item x_k.
  - $p^i_{jk} = 0$ indicates that the item x_k is absolutely preferred over item x_j.
  - $p^i_{jk} > 1/2$ indicates that x_j is preferred over item x_k.

  Another widely applied approach is *linguistic preference relations*, using a linguistic term set to represent the preference intensity of the items. If $D = S$ where S is a linguistic term set $S = s_0, \ldots, s_g$ with odd cardinality $(g + 1)$, $s_g/2$ being a neutral label (e.g., "*equally preferred*") and the remaining labels p^i_{jk} in the matrix P^i represent the linguistic preference intensity of x_j over x_k.

3.3 Consensus-achieving process

In group decision-making, the selection process does not guarantee a high agreement level in the final decision, which is essential in many real-life situations (Castro et al. 2015). To overcome this drawback, a consensus-achieving process is needed to modify the initial preferences of group members in a discussion process and make them closer to a collective opinion that is satisfactory for all group members.

Consensus can be understood as a state of mutual agreement where the final decision satisfies all group members (Rothstein and Butler 1987). *Consensus measures* describe the consensus level between group members. These measures are in the [0, 1] interval, where 0 means no consensus and 1 means full consensus. The remaining assessment values are in (0, 1), representing partial consensus degrees. Based on these values, the consensus concept can be interpreted from different points of view, ranging from strict to softer interpretations. *Strict consensus (unanimity)* indicates a full agreement for all group members (i.e., consensus measure is equal to 1), which is usually very hard and too costly to achieve (Palomeres et al. 2011; Herrera-Viedma et al. 2014). *Soft consensus* has been proposed to soften strict consensus, where the consensus concept is defined using *fuzzy linguistic quantifiers*.

The consensus-achieving process is dynamic and repeated. It attempts to obtain a high agreement of group members before making the final decision. This process can be performed in the following phases (Castro et al. 2015; Gallardo et al. 2015):

– *Phase 1* (Preference gathering and consensus measures): The preferences of individual group members are gathered to calculate the current consensus degree by means of *consensus measures*. This phase cares about different consensus measures to determine the agreement in the group. The adequate selection of a consensus measure is a key issue for improving and optimizing the consensus-achieving process (Palomeres et al. 2011).
– *Phase 2* (Consensus control): The current consensus degree is compared with the *consensus threshold* defined at the beginning of the consensus-achieving process. If the consensus degree exceeds the consensus threshold, then the consensus-achieving process finishes. Otherwise, this process repeats until achieving a consensus or reaching the maximum number of iteration rounds defined earlier.
– *Phase 3* (Consensus progress): To increase the group's agreement level and accelerate the consensus-achieving process, different procedures need to be performed based on the capability of the consensus model. Typically, two procedures can be performed: (1) allowing group members to adapt their preferences based on the generated feedback and (2) supporting automatic preference update mechanisms:
    - *Feedback generation* (Bryson 1996; Carlsson et al. 1992; Dong and Zhang 2014; Mata et al. 2009): The consensus model implements a feedback mechanism that sends feedback to the moderator who supports group members in modifying their preferences and brings them closer to the group opinion.
    - *Automatic updates* (Ben-Arieh and Chen 2006; Wu and Xu 2012; Zhang et al. 2011): The consensus model implements approaches allowing group members to provide their initial preferences. Thereafter, an automated preference adaptation mechanism is applied to increase the agreement level.

4 Consensus models for group decision-making

As mentioned in Sect. 3.3, *full consensus* is usually tough to reach. Therefore, more realistic consensus models have been proposed following the *soft consensus* concept. These models have been widely used since they are more human-consistent and ideal for reflecting human perceptions of the meaning of consensus in practice (Kacprzyk and Fedrizzi 1988; Herrera-Viedma et al. 2014). Following the concept of soft consensus, we discuss in this section innovative and prominent consensus models found in the literature based on different methods: reference domain (Sect. 4.1), coincidence method (Sect. 4.2), OWA operators (Sect. 4.3), guidance measures (Sect. 4.4), recommendation generation (Sect. 4.5), and individual centrality (Sect. 4.6). The existing studies presented in these sections are classified based on the categorization approaches proposed by Herrera-Viedma et al. (2014) and Cabrerizo et al. (2017b). However, differing from these two studies, we introduce further consensus models published from 2017 to provide a broader landscape of the literature (see Sects. 4.3 and 4.4). We also discuss consensus models that better support group decision-making processes in heterogeneous and large-scale groups (see Sect. 4.7). Besides, to provide readers with better guidance for using these consensus methods, we discuss group decision-making scenarios where the consensus model can be applied and the main idea of related consensus approaches. Simple examples are also included to provide readers with a better understanding of the mentioned scenarios and concepts. We also add a short *remark* at the end of each section, summarizing the presented approaches and discussing their advantages and limitations. The summary of the mentioned consensus models is shown in Tables 1 and 2. Due to a high number of related studies in the literature and their solid content, we do not present the details of the related consensus models. Instead, we discuss only the basic concepts and main ideas of the models and refer readers to the related studies for further details.

4.1 Consensus model based on reference domain

4.1.1 When to apply?

The consensus model based on reference domain supports a consensus-achieving process of group decision-making problems in the following settings:

- Fuzzy preference relations are used to elicit group members' preferences. Group members present their preferences for potential items using fuzzy preference relations. For instance, in the requirements engineering domain, the preference of a stakeholder s_1 for a set of three requirements $\{r_1, r_2, r_3\}$ can be represented in matrix P_1 shown below. The value 0.8 indicates that $p^1_{12} = 0.8$, meaning that the stakeholder prefers requirement r_1 over requirement r_2 (see also Sect. 3.2).

$$P_1 = \begin{bmatrix} 0.5 & \mathbf{0.8} & 0.5 \\ 0.2 & 0.5 & 0.7 \\ 0.5 & 0.3 & 0.5 \end{bmatrix}$$

- Some group members/items have higher importance than others. For instance, in a software engineering scenario, the project manager and domain experts might impact the final group decision more than others. Besides, some requirements may have a higher priority (i.e., should be implemented earlier) than others.
- The difference in the initial preferences of group members is high, which makes the group far from consensus.

Table 1 Application scenarios and main ideas of consensus models for group decision-making

Consensus model	When to apply?	Main ideas
Consensus model based on *reference domain* (Sect. 4.1)	Group members' preferences are elicited using fuzzy preference relations; some group members/items have a higher importance than others; high differences in initial preferences of group members	Compute consensus measures based on the reference domain
Consensus model based on the *coincidence method* (Sect. 4.2)	Group members specify their preferences for items using linguistic terms	Calculate the consensus degree depending on the coincidence concept
Consensus model using *OWA operators* (Sect. 4.3)	Group members express their preferences for items using linguistic preference relation; preferences are specified under multiple criteria	Calculate a collective consensus degree using aggregation operators
Consensus model based on *guidance measures* (Sect. 4.4)	Insufficient knowledge of group members (1) and complex and inconsistent group decisions (2)	For *(1)*: the consensus-achieving process is guided by consensus degrees and proximity degrees For *(2)*: the consensus-achieving process is guided by a measure combining consistency and consensus measures
Consensus model based on recommendation generation (Sect. 4.5)	A moderator supervises the consensus-achieving process	Integrate a dynamic or semi-automated feedback mechanism into the consensus-achieving process
Consensus model based on individual centrality (Sect. 4.6)	Social factors are considered in the group decision-making process; items are evaluated according to different criteria	Group members select a leader according to their trust in the leader and the leader's expertise
Consensus model for LS-GDM newline (Sect. 4.7)	Group size is relatively or very large; decision attributes are complex; group members' preferences are fuzzy and uncertain	*Method 1*: classify group members into subgroups according to their preferences *Method 2*: model group members' preferences together with attitude; deal with group members who did not contribute to the consensus; identify minority opinions that hinder the consensus-achieving process; construct an interactive consensus model; a moderator or representatives of subgroups guide the consensus-achieving process *Method 3*: develop LS-GDM support systems

Table 2 Summary of consensus models for group decision-making

Consensus model		Related work
Reference domain (Sect. 4.1)	Group members as the reference domain	Carlsson et al. (1992), Fedrizzi et al. (1988), Kacprzyk and Fedrizzi (1988), Kacprzyk et al. (1992), Kacprzyk and Fedrizzi (1989)
	Items as the reference domain	Cabrerizo et al. (2009a), Cabrerizo et al. (2017b), Herrera et al. (1996), Herrera et al. (1997), Herrera-Viedma et al. (2005), Herrera-Viedma et al. (2007), Cabrerizo et al. (2010), Herrera-Viedma et al. (2014)
Coincidence method (Sect. 4.2)	Strict coincidence among group members' preferences	Cabrerizo et al. (2017a), Fedrizzi and Kacprzyk (1993), Herrera et al. (1996), Herrera et al. (1997), Kacprzyk (1987), Kacprzyk (1986), Kacprzyk and Fedrizzi (1988), Mich et al. (1993)
	Soft coincidence among group members' preferences	Bordogna et al. (1995), Cabrerizo et al. (2017a), Fedrizzi and Mich (1992), Fedrizzi and Kacprzyk (1993), Kacprzyk (1987), Kacprzyk (1986), Kacprzyk and Fedrizzi (1988), Chen et al. (2012)
	Coincidence among solutions	Ben-Arieh and Chen (2006), Herrera-Viedma et al. (2002)
OWA operators (Sect. 4.3)	Using OWA operators to determine agreement positions among group members	Csiszar (2021), He et al. (2021), Kuncheva and Krishnapuram (1996), Merigo and Gil-Lafuente (2009), Merigó and Casanovas (2011), Palomeres et al. (2011)
Guidance measures (Sect. 4.4)	Resolving domain-knowledge missing issues	Cabrerizo et al. (2009b)
	Computing guidance measures by combining consistency and consensus measures	Cabrerizo et al. (2010), Cabrerizo et al. (2017b), Herrera et al. (1997), Herrera-Viedma et al. (2007), Rodríguez et al. (2012), Zhang et al. (2014), Zhao et al. (2018)

Table 2 continued

Consensus model		Related work
Recommendation generation (Sect. 4.5)	Basis approaches focusing on the moderator	Herrera et al. (1996), Herrera et al. (1997), Kacprzyk (1986), Kacprzyk and Fedrizzi (1988), Kacprzyk et al. (1992)
	Dynamic feedback mechanism substituting the moderator's actions	Herrera-Viedma et al. (2002), Herrera-Viedma et al. (2005), Herrera-Viedma et al. (2007)
	Better analysis tools to support more effective and efficient decision-making processes	Kacprzyk et al. (2009), Kacprzyk et al. (2010)
	Semi-automated feedback mechanisms	Bouzarour-Amokrane et al. (2015)
Individual centrality (Sect. 4.6)	Selecting a user as a decision bench-maker and compare the preference similarity between this user and others	Tundjungsari et al. (2012)
Consensus models for LS-GDM (Sect. 4.7)	Clustering methods in LS-GDM	Liu et al. (2014); Zahir (1999a)
	Consensus-achieving processes in LS-GDM	Dong et al. (2016), Palomares et al. (2014a), Palomares et al. (2014b), Quesada et al. (2015), Xu et al. (2015), Wu and Xu (2018)
	LS-GDM support systems	Carvalho et al. (2008), Palomares et al. (2014b), Turoff et al. (2002)

4.1.2 Basic concepts

The main idea of the consensus model is to compute the consensus measures based on the *reference domain* selected for the calculation process.

The reference domain can be *a set of individual group members* or *a set of items*. The computed consensus measure expresses the degree to which, *"**most** of the **important** individual group members agree with **almost all** of the **relevant** items"* (Kacprzyk and Fedrizzi 1988). This expression uses fuzzy linguistic quantifiers such as *"most"* and *"almost all"*. Besides, fuzzy sets such as *"important"* and *"relevant"* are utilized to denote the importance/relevance of the individual group members and items (Zadeh 1983).

The set of group members as the reference domain: This approach was proposed in very early studies such as (Carlsson et al. 1992; Fedrizzi et al. 1988; Kacprzyk and Fedrizzi 1988; Kacprzyk et al. 1992; Kacprzyk and Fedrizzi 1989) that calculate the consensus measure in three steps:

- *Step 1*: For each pair of individual group members, the agreement degree of their preferences between all pairs of items is calculated.
- *Step 2*: The agreement degrees calculated in *Step 1* are pooled to obtain a degree of agreement of all the pairs of individuals regarding their preferences between the *"most"* relevant pairs of items.
- *Step 3*: The agreement degrees calculated in *Step 2* are merged to obtain a degree of agreement of *"almost all"* important pairs of individuals w.r.t their preferences between *"relevant"* pairs of items. The outcome reflects the consensus degree of the whole group.

The set of items as the reference domain: Other studies such as (Herrera et al. 1996, 1997; Cabrerizo et al. 2010; Herrera-Viedma et al. 2007; Cabrerizo et al. 2009a; Herrera-Viedma et al. 2005) propose various approaches focusing on the item set. These approaches compute the consensus measures by considering the following levels of a preference relation (Cabrerizo et al. 2017b; Herrera et al. 1996; Herrera-Viedma et al. 2014):

(1) *The level of preference* indicates the consensus degree among all the m preference values specified by n group members.
(2) *The level of item* measures the consensus existing over all pairs of items where a given item is present. For instance, a group decision must be made for a list of three requirements r_1, r_2, and r_3. Given requirement r_1, all pairs from r_1 to the remaining requirements ((r_1, r_2) and (r_1, r_3)) are considered when measuring the consensus.
(3) *The level of preference relation* evaluates the social consensus indicating the current consensus in terms of preferences among all group members.

The calculated consensus measures help to understand the current consensus status in each representation level, on which group members who are close to consensus or have more trouble reaching consensus are identified.

Remark When comparing the two mentioned approaches, Cabrerizo et al. (2017b) and Herrera-Viedma et al. (2014)) found out that the approach focusing on the set of

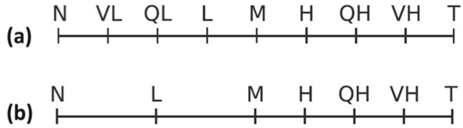


Fig. 2 Examples of symmetric fuzzy linguistic term sets (**a**) and unbalanced fuzzy linguistic term sets (**b**), where None = N, Very Low = VL, Quite Low = QL, Low = L, Medium = M, High = H, Quite High = QH, Very high = VH, and Total = T

items works better in terms of consensus process design and allows to guide group members to modify their opinions during the discussion process.

4.2 Consensus model based on the coincidence method

4.2.1 When to apply?

The consensus model based on the coincidence method supports the consensus-achieving process of group decision-making problems where group members may find it difficult to express their preferences using numerical values (Bryson 1996; Kacprzyk 1986; Kacprzyk and Fedrizzi 1988; Herrera-Viedma et al. 2007). This is especially the case in *multi-attribute group decision-making problems*, where group members specify their preferences for a set of potential items according to a set of criteria/attributes. In this context, instead of using numerical values, group members prefer using natural language (e.g., *linguistic terms*) to express assessments that are normally vague, imprecise, and incomplete (Rodríguez et al. 2012; Porro et al. 2021). Based on this idea, group decision-making scenarios need to be defined in *fuzzy linguistic contexts* and group members convey their preferences using linguistic variables assessed in linguistic term sets. The linguistic terms are uniformly and symmetrically distributed, i.e., the same discrimination levels on both sides of the mid-linguistic term are specified (Alonso et al. 2013; Cabrerizo et al. 2015; Dong et al. 2013). An example of a symmetric linguistic term set is the following: None = N, Very Low = VL, Quite Low = QL, Low = L, Medium = M, High = H, Quite High = QH, Very high = VH, Total = T (see Fig. 2a).

Besides, this consensus method can also be applied to group decisions where group members need to express their opinions using linguistic term sets that are not uniformly and symmetrically distributed (Alonso et al. 2008; Cabrerizo et al. 2009b; Alonso et al. 2008). The unbalanced fuzzy linguistic information could appear when group members need to assess their preferences with several terms on one side of the reference domain higher than on another side (see an example in Fig. 2b).

4.2.2 Basic concepts

The main idea of the model is to calculate the consensus degree [i.e., the similarity between group members' preferences (Cabrerizo et al. 2017b)] using one of the following approaches depending on the coincidence concept (Herrera et al. 1997):

Approach 1—Strict idea of the coincidence concept (Cabrerizo et al. 2017a; Fedrizzi and Kacprzyk 1993; Herrera et al. 1996, 1997; Kacprzyk 1987, 1986; Kacprzyk and Fedrizzi 1988; Mich et al. 1993): If the opinions of two group members are the same then they are in agreement (consensus degree = 1). Otherwise, they are in disagreement (consensus degree = 0).

Approach 2: The less strict idea of the coincidence concept (Bordogna et al. 1995; Cabrerizo et al. 2017a; Fedrizzi and Mich 1992; Fedrizzi and Kacprzyk 1993; Kacprzyk 1987, 1986; Kacprzyk and Fedrizzi 1988; Chen et al. 2012): If the opinions of two group members are more or less the same according to a *pre-defined degree* α, then they are in agreement (consensus degree = 1). Otherwise, they are in disagreement (consensus degree = 0).

Approach 3—Another less strict idea of the coincidence concept (Ben-Arieh and Chen 2006; Herrera-Viedma et al. 2002): The coincidence concept in this approach is a gradual concept assessed with different values in the unit interval [0, 1], expressing the closeness level between two group members' opinions.

Remark Each of the mentioned approaches shows its strengths and drawbacks. The advantage of the first approach is the simplicity and easiness of the similarity computation. However, it faces a disadvantage when the obtained consensus degree does not reflect the real consensus situation. The positive side of the second approach is that the obtained consensus degree better reflects the actual consensus situation. However, the limitation lies in difficulties when computing the consensus degree. Particularly, the similarity criteria to calculate consensus measures need to be defined, which is hard or even impossible sometimes. Finally, the last approach shows the strength in achieving a consensus degree that does not show group members' preferences but the position of the items in a solution, which reflects the real consensus situation in each round of the consensus-achieving process. The drawback of this approach is that the calculation of the consensus degrees is more complicated than the two previously mentioned approaches since we need to define to which extent the opinions of group members are close to each other (Cabrerizo et al. 2017b).

Besides, when comparing the three mentioned approaches, Cabrerizo et al. (2017b) and Herrera-Viedma et al. (2014) claim that the second and the third approach are the most useful methods since they provide group members with advice during the consensus-achieving process. Besides, they show that the second approach is helpful, especially in group decision-making scenarios under preference relations. The third approach is suitable for decisions where the preferences of group members are represented in different formats.

4.3 Consensus model using order-weighted averaging operators

4.3.1 When to apply?

The consensus model using order-weighted averaging operators supports the consensus-achieving process of group decisions where group members have expressed their preferences utilizing *linguistic preference relation* and their preferences should be specified under multiple criteria, multiple attributes, or multi-objective optimization (Palomeres et al. 2011). For instance, in the software engineering domain, a group of developers must decide on a programming language for a project. The potential programming languages in this scenario are Python, Java, and C++. A developer can create a preference relation between these languages according to various criteria, such as *familiarity, simplicity, performance, availability of tools and libraries,* and *community support*. Assume that, in terms of familiarity, developer u_1 finds that Python is the most familiar, followed by Java and then C++. He/she can represent this preference relation as follows: Python > Java > C++. The symbol "$>$" represents the "preferred to" relation. This preference relation indicates that developer u_1 prefers Python over Java, and he/she prefers Java over C++.

4.3.2 Basic concepts

The main idea of this model is to calculate a collective consensus degree of a group using *aggregation operators* (Kuncheva and Krishnapuram 1996; Palomeres et al. 2011). This model also describes the general idea of group decisions where the preferences of group members need to be merged in the consensus-achieving process (Csiszar 2021; Palomeres et al. 2011).

Ordered Weighted Averaging (OWA) is a typical example of aggregation operators. It is a symmetric aggregation function that allocates weights according to the input value and unifies the conjunctive and disjunctive behavior in one operator (Yager 1988). Formally, an OWA operator of dimension n is the mapping $F : I_n \rightarrow I$ if it has an associated weighting vector $w = (w_1, w_2, \ldots, w_n)$, $w_i \in [0, 1]$, $1 \leq i \leq n$ with $\sum_{i=1}^{n} w_i = 1$ and $F(x_1, x_2, \ldots, x_n) = OWA_w(x) = w_1 x_{(1)} + w_2 x_{(2)} + ... + w_n x_{(n)}$, where $x_{(j)}$ is the j^th largest element of the bag $< x_1, \ldots, x_n >$. The fundamental aspect of an OWA operator is the reordering action, meaning that the weights w_i are associated with a particular ordered position rather than with a particular element. Besides, different OWA operators are distinguished by their weighting functions that are defined as follows:

- Max: $w_* = (1, 0, \ldots, 0)$ and $F_{max}(x_1, \ldots, x_n) = max(x_1, \ldots, x_n)$
- Min: $w^* = (1, 0, \ldots, 0)$ and $F_{max}(x_1, \ldots, x_n) = max(x_1, \ldots, x_n)$
- Arithmetic mean: $w_A = (1/n, 1/n, \ldots, 1/n)$ and $F_A = ((x_1 + ... + x_n)/n)$

OWA operators provide a parameterized family of aggregation functions, including well-known operators such as the *Attribute OWA (AOWA), Centered OWA (COWA), Weighted OWA (WOWA), Generalized OWA (GOWA)*, and *Distance OWA (DOWA)*. For further details of these operators and their extensions, we refer to Csiszar (2021), He et al. (2021), Merigo and Gil-Lafuente (2009), Merigó and Casanovas (2011).

Remark In the aggregation process, it is extremely important to reflect the group's decision policies or *the group's attitudes* regarding how to measure consensus as faithfully as possible (Palomeres et al. 2011). Among the above-mentioned operators, *AOWA* has been proposed as an operator that can integrate the concept of group attitude towards consensus in the consensus measures used throughout the consensus-achieving process. *Group attitude* can be reflected by three different *attitudinal parameters* $\in [0, 1]$.

The first parameter (*orness*) represents the group's attitude in aggregating pairwise similarities. This attitude can be either *optimistic* if it is greater than 0.5, *pessimistic* if it is smaller than 0.5, or *neutral* if it is equal to 0.5. The second parameter (α) indicates whether higher or lower similarity values are assigned to a non-null weight when aggregating. The lower α, the higher ranked values are considered. Finally, *the third parameter (d)* indicates the number of similarity values given a non-null weight and therefore are considered in the aggregation. We refer to Palomeres et al. (2011) for further details of the mentioned approach.

4.4 Consensus model based on guidance measures

4.4.1 When to apply?

The consensus model based on guidance measures supports the consensus-achieving process of group decisions with the following settings:

- Insufficient knowledge of group members: In some scenarios where some group members do not have enough knowledge about the domain and therefore cannot discriminate the degree to which some options are better than others (Atas et al. 2018). These stakeholders tend to provide incomplete information rather than trying to specify their preferences using fuzzy linguistic term sets. In this context, *incomplete unbalanced fuzzy linguistic preference relations* (*IUFLPR*) can be used by group members to provide their preferences (Cabrerizo et al. 2009b). One example of these preference relations is described as follows. Assume that a group of three developers is evaluating three different web frameworks: *Django, Ruby on Rails,* and *Express.js*. The developers are asked to provide their preferred relation for the three frameworks based on their experience. However, not all group members have experience with all three frameworks. The preference relation provided by the group members are the following:

  Developer 1: Django > Ruby on Rail;
  Developer 2: Express.js > Ruby on Rails > Django;
  Developer 3: Django > Express.js

  In this example, the preference relation is *incomplete* since not all group members have provided a preference for all three mentioned frameworks. Additionally, the preference relation is *unbalanced* because some frameworks have more preference statements than others. In fact, *Django* and *Ruby on Rails* have two preference statements each, while *Express.js* has three preference statements.

- Complex and inconsistent group decisions: Group decision-making problems can be complex and consist of inconsistencies among group members' preferences. In such scenarios, inconsistencies must be quantified and monitored, which will then be used as a parameter to validate the final solution obtained after the consensus-achieving process (Cabrerizo et al. 2017b; Chiclana et al. 2007; Fedrizzi et al. 2002; Herrera et al. 1997; Herrera-Viedma et al. 2014; Wu and Xu 2012).

4.4.2 Basic concepts

For group decisions where group members lack domain knowledge, the consensus-achieving process can be guided by two types of measures: (1) *consensus degrees* that evaluate the agreement level of all group members and (2) *proximity measures* that evaluate the agreement level between the group members' preferences and the group preference (Cabrerizo et al. 2009b). These measures are estimated based on Tanino's consistency principle (Tanino 1984) and use all its estimation possibilities. Besides, missing preference values in a group member's *IUFLPR* are computed using the preference values provided by him/her. This assures that the reconstruction of *IUFLPR* is compatible with the rest of the information provided by the group member.

For complex and inconsistent group decisions, the consensus-achieving process can be guided by a measure that combines consistency and consensus measures (Cabrerizo et al. 2010, 2017b; Herrera et al. 1997; Herrera-Viedma et al. 2007; Zhang et al. 2014; Zhao et al. 2018). Such measure can be computed as a weighted aggregation of consistency and consensus degrees. Thereafter, the measure is used as a control parameter to decide if the consensus-achieving process is completed. Adopting consistency measures in the consensus-achieving process can help to avoid misleading solutions that could not be detected using the approaches with only consensus degrees (Cabrerizo et al. 2017b; Herrera-Viedma et al. 2014). Another approach is to adapt consistency and consensus degrees with *hesitant fuzzy linguistic preference relations (HFLPRs)* based on discrete fuzzy numbers (Rodríguez et al. 2012). When group members are confronted with more complex subjective information, they tend to be hesitant about linguistic variables such as *"better than good"*, *"between fair and very good"*, or even more complex expressions. In such scenarios, the concept of *a hesitant fuzzy linguistic term set* helps to increase the flexibility and richness of linguistic elicitation in hesitant situations under qualitative settings. In this context, a direct consensus-achieving process is developed to assist group members who must reconsider their preferences for achieving the pre-defined consensus degree. We refer to Cabrerizo et al. (2017b), Rodríguez et al. (2012), Herrera-Viedma et al. (2014) for more details about these approaches.

In another work, Zhang et al. (2014) study consistency and consensus measures for group decision-making problems that support the concept of *distribution assessments*. Distribution assessments in a linguistic term set enable the assignment of symbolic proportions to all the linguistic terms. One example of distribution assessments is the following (Zhang et al. 2014): Let assume that the term set $S = \{s_{-2} =$ "$very\ poor$", $s_{-1} =$ "$poor$", $s_0 =$ "$average$", $s_1 =$ "$good$", $s_2 =$ "$very\ good$" $\}$ are used by a football coach to evaluate the level of a player. The player participated in *ten* football matches, in which he was judged *five times* as s_2, *two times* as s_1, and *three times* as s_{-1}. The coach's evaluations for the player can be described as distribution assessments of S as follows: $\{(S_{-2}, 0), (S_{-1}, 0.3), (S_0, 0), (S_1, 0.2), (S_2, 0.5)\}$. The consensus model developed in this work has effectively improved the consensus level among distribution linguistics preference relations.

Remark The mentioned approaches point out that taking into account additional criteria, such as consistency measures in the consensus-achieving process, can help to achieve more adequate solutions for a group decision-making problem. For instance, using consistency measures helps to avoid misleading solutions, which cannot be detected in consensus models where only consensus degrees are considered (Cabrerizo et al. 2017b).

4.5 Consensus model based on recommendation generation

4.5.1 When to apply?

The consensus model based on recommendation generation supports consensus-achieving processes where a moderator is responsible for monitoring the agreement in each stage and supervising the decision process towards success (Herrera-Viedma et al. 2014; Cabrerizo et al. 2017b).

4.5.2 Basic concepts

In the mentioned group decisions, recommendation generation methods play a crucial role. Earlier related studies propose approaches focusing on a moderator (Herrera et al. 1996, 1997; Kacprzyk 1986; Kacprzyk and Fedrizzi 1988; Kacprzyk et al. 1992). The common idea is to calculate consensus measures that help to enhance the moderator's knowledge about the current consensus situation. Besides, the moderator utilizes these measures to monitor the consensus-achieving process. However, these studies show a limitation since the moderator can introduce some subjectivity (Cabrerizo et al. 2017b; Herrera-Viedma et al. 2014). Different models have been proposed to overcome this drawback. These models integrate a dynamic feedback mechanism into the consensus-achieving process, substitute the moderator's actions, and provide the moderator with better analysis tools. This way, the proposed models can support more effective and efficient decision-making processes (Kacprzyk et al. 2009, 2010; Herrera-Viedma et al. 2002, 2005, 2007). Besides, there exist other consensus approaches with a *semi-automated feedback mechanism* that supports an automatic feedback mechanism, allows the moderator's intervention, and considers the importance of group members (Bouzarour-Amokrane et al. 2015). The main idea of the mentioned approaches is presented in the following.

Dynamic feedback mechanism substituting the moderator's actions: The consensus model consists of two measures: *consensus* and *proximity*. A *consensus measure* indicates the agreement between experts' opinions, while a *proximity measure* shows how far the individual opinions are from the group opinion. These measures are calculated by comparing the positions of the items between the preferences of group members and the preference of the whole group. Based on these measures, a consensus support system is developed to substitute the moderator's actions. The consensus measure guides the consensus-achieving process until the final solution is obtained. The proximity measure guides the discussion phases and helps group members change their opinions to obtain a high consensus. For further details, we refer to

Herrera-Viedma et al. (2002), Herrera-Viedma et al. (2005), Herrera-Viedma et al. (2007).

Better analysis tools for more effective and efficient decision-making processes: This approach uses *action rules* to generate advice for the further running of discussions in a group. The concept of an *action rule* is presented by Ras and Wieczorkowska (2000) in the context of *Pawlak's information systems* (Pawlak 1981). It is represented by triples $IS = \{O, A, V\}$, where O is a finite set of objects, A is a set of its attributes, and $V = \bigcup_a V_a$ with V_a being a domain of an attribute $a \in A$. The set of attributes A may be partitioned into subsets of *stable* (A_{St}) and *flexible* attributes (A_{Fl}). The intended meaning of an action rule is to show how a subset of *flexible* attributes should be changed to obtain the expected changes of the decision attribute for a subset of objects characterized by stable attributes. For instance, let bank customers be objects $o_i \in O$ characterized by *stable attributes* (e.g., *age, gender,* and *profession*) and *flexible attributes* (e.g., *account type* and *reduction of the monthly fee*) and the decision attribute is the customer's *total monthly spending*. In this context, an action rule may indicate that, e.g., offering a 20% of monthly fee reduction (instead of the option with 10%) to a middle-aged customer is expected to increase his/her spending from medium to high. We refer to Kacprzyk et al. (2009), Kacprzyk et al. (2010) for further details.

Semi-automated feedback mechanism: This approach supports a more realistic model by integrating different human behavior aspects (e.g., positive and negative influences, selfishness, and prudence) in the evaluation and recommendation phases. This approach is developed based on a general framework of the *bipolar approach* (Tchangani et al. 2012), in which initial group members' preferences are represented by bipolar measures expressing the degree of *supportability* and *rejectability* of items. Besides, the *satisficing game theory* is used as an aggregation tool in individual group members' evaluations. This theory is based on the fact that decision-makers do not necessarily seek an optimal solution (that usually costs too much effort), but instead, a satisfactory solution whose capabilities are estimated fairly good regarding objectives achievement (Tchangani 2009). This way, the theory provides adequate tools for selecting satisficing items and reaching a consensus. We refer to Bouzarour-Amokrane et al. (2015) for further details.

Remark Compared to other studies in the same research line, the *consensus approach based on dynamic feedback mechanism* supports an automatic consensus-achieving process without the moderator, which avoids a possible subjectivity that the moderator can introduce. Besides, approaches using the concept of *action rules* help to provide useful information regarding the consensus-achieving process, such as how far the group is from consensus, what are the most controversial items, whose preferences are in the highest disagreement with the rest of the group, and how their preference changes would affect the consensus degree. Finally, the consensus approach supporting a *semi-automated feedback mechanism based on the bipolar concept* is similar to the two previous approaches in the sense that the consensus-achieving process consists of the adaptions of group members' initial assessments to obtain consensus solutions. However, the difference is that this approach does not converge the assessments of individual group members on the set of all items but focuses mainly on items that receive the same initial rating behavior of group members. Targeted recommendations are then given to divergent group members (with incoherent opinions compared to others) in the adaptive process. Another difference is that the importance degree of group members is considered in the evaluation and recommendation phase.

4.6 Consensus model based on individual centrality

4.6.1 When to apply?

The consensus model based on individual centrality supports the consensus-achieving process of group decisions where social aspects such as trust, reputation, and social judgment scheme are taken into account during the group decision-making process. Besides, in these decisions, items are evaluated according to different criteria. For instance, in the requirements engineering domain, stakeholders evaluate the requirements based on popular criteria such as *effort, profit*, and *risk*.

4.6.2 Basic concepts

The main idea of this model is to allow group members to select *a leader* according to some social aspects, such as the trust of other group members in the leader and the leader's reputation and expertise (Tundjungsari et al. 2012). The leader is a so-called *Supra Decision Maker* (SDM) who plays a role as a decision bench-maker to other group members in evaluating each item. The more the preference similarity between the SDM and other group members, the higher the probability of reaching a consensus. In this approach, the consensus-achieving process follows the idea of the three primary phases mentioned in Sect. 3.3 but adds some changes corresponding to the concept of the SDM. These three phases are summarized in the following:

- *Phase 1 (Preference gathering and consensus measure)*: Group members have to provide their preferences for a set of items according to a set of criteria. Besides, they need to specify the weight/importance $\in [0, 1]$ for each criterion. The sum of all the weights should be equal to 1. Thereafter, one group member is selected as the SDM. The distance between a group member u_i and the SDM ($d(SDM, u_i)$) is calculated using the *Euclidian-like distance* (Rusinowska et al. 2007). The distance measure determines whether a group member has achieved a consensus level (the shorter the distance to the SDM, the better). If not, this group member must adapt his/her preferences for the item. In this approach, the SDM cannot change his/her preference since he/she has been chosen by trust and reputation mechanisms as the leader/advisor of the group for having the highest reputation value.
- *Phase 2 (Consensus control)*: A consensus level θ is pre-defined by the group, such that $\theta = 1 - d_{max}$, where $d_{max} = max\{d(SDM, u_i)\}$ denotes the *maximum allowance distance* from the SDM to the group members. Suppose the distance between the SDM and a group member u_i ($d(SDM, u_i)$) is greater than d_{max}. In that case, this group member has to change his/her preferences until the majority of his/her decision toward all items has reached the consensus level. For each group

member, when half of the items have reached the consensus level, the consensus for him/her has been achieved.
- *Phase 3(Consensus progress)*: Group members who did not contribute to the consensus process or did not have enough items reaching the consensus level (in *Phase 2*) will receive feedback concerning preference adaptations based on shortening the distance between them and the SDM.

Remark By taking into account social aspects and group members' evaluations for items performed according to multiple criteria, the mentioned consensus model contributes to a better understanding of consensus achievement within a group decision-making setting, which is the prerequisite to achieving a better quality decision (Tundjungsari et al. 2012).

4.7 Consensus models for heterogeneous and large-scale groups

4.7.1 When to apply?

The expansion of societal and technological paradigms such as e-democracy (Kim 2008), social networks (Urena et al. 2019), marketplace selection for group shopping (Büyüközkan 2004), and adding new requirements to the solution of consensus-based group decision-making problems (Palomares et al. 2014a) has triggered the engagement of a large number of users in different decision-making problems. For this reason, large-scale group decision-making (LS-GDM) has become an interesting topic in the decision-making problem research line (Rodríguez et al. 2018).

Differing from classical consensus-achieving models that focus on achieving an agreement within a group of a few users, LS-GDM consensus models are applied to group decisions with the following settings (Chen and Liu 2006; Gou et al. 2018; Liu et al. 2014; Pan et al. 2022; Rodríguez et al. 2018; Srdjevic 2007; Tang et al. 2021; Xiao et al. 2020; Tang and Liao 2021; Yager 2001; Zahir 1999a; Zhang et al. 2020):

- Group size is relatively large [(e.g., more than 20 users (Chen and Liu 2006; Srdjevic 2007), several hundreds, or even thousands of users (Rodríguez et al. 2018)].
- Groups are heterogeneous, composing of individuals with diverse characteristics, such as different ages, genders, cultures, education levels, backgrounds, and opinions. These groups are characterized by a high degree of diversity among their members, which can lead to different preferences and decision-making processes.
- The decision attributes tend to be complex due to their large size and the connections among group members. In this context, group members must specify their preference for items based on multiple and complex criteria. Tang and Liao (2021) discuss a group decision-making scenario where many experts have to select a pilot eco-industrial park in the Sichuan Province, China. In this scenario, a large group of experts from multiple fields and ministries must be invited to make decisions according to multiple attributes. For instance, eight ministries in China, including the National Development and Reform Commission (NDRC), the State Environmental Protection Administration (SEPA), the Ministry of Science and Technology, the Ministry of Industry and Information Technology, the Ministry

of Finance, the Ministry of Commerce and the National Bureau of Statistics. The list of alternatives is also big in this scenario (more than 40 candidates have been selected). The experts must discuss and evaluate the alternatives according to complex attributes, such as sharing common services and infrastructures, industrial trade by-products, manufacturing waste, energy, heat, and wastewater. Furthermore, for each attribute, different aspects also need to be considered. For instance, to evaluate the impacts of wastewater on the environment, different aspects have to be considered, such as water and habitat contamination, soil degradation, and harmful substances.

– Group members' preferences tend to be fuzzy and uncertain due to the complexity of the decision-making problems.

Due to the mentioned settings, the main concerns emerging in these group decisions are scalability, time cost, constant preference supervision, stronger disagreement positions, and difficulties in understanding and visualizing the current status of group consensus (Labella et al. 2018; Palomares et al. 2014b; Rodríguez et al. 2012).

4.7.2 Basic concepts

Plenty of attempts have been made on LS-GDM with the focus on the following major methods (Rodríguez et al. 2018): clustering methods in LS-GDM (Liu et al. 2014; Zahir 1999a), consensus-achieving processes in LS-GDM (Dong et al. 2016; Palomares et al. 2014a, b; Quesada et al. 2015; Xu et al. 2015; Wu and Xu 2018), and LS-GDM support systems (Carvalho et al. 2008; Palomares et al. 2014b; Turoff et al. 2002). We summarize the main idea of these methods in the following.

a. Clustering methods in LS-GDM: The main idea is to classify group members in LS-GDM problems into several subgroups/clusters according to their evaluations/preferences in order to process more easily a high number of evaluations or preferences provided by group members. Based on this idea, several clustering approaches have been developed.

One early approach proposed by Zahir (1999a) presents an algorithm to classify group individuals into natural clusters using a convenient similarity measure. In this work, the author denotes a large group with clusters an *ensemble* and extends the conventional *Analytic Hierarchy Process (AHP)* formulations (Saaty 1990)[7] to an *Euclidean vector space* and applies it to group decision of a homogeneous group. The proposed algorithm takes advantage of the benefits of Euclidean embedding in an interesting manner. Once the clustering structure of a group has been established, the author extends the simple mechanism proposed in his previous work (Zahir 1999b) that aggregates the preferences of homogeneous groups to cluster and calculate the priorities representing the entire group.

Another approach proposed by Liu et al. (2014) combines *interest groups* with the practical decision information to classify group members in *complex multi-attribute large-group decision-making (CMALGDM) problems* in an *interval-valued intuitionistic fuzzy (IVIF) environment*. *CMALGDM* is one of the most common activities in

[7] The concept of *Analytic Hierarchy Process* is presented by Saaty (1990), which has been commonly engaged to aid individuals as well as group decision-making processes.

modern society, involving the selection of an optimal item from a finite set of items evaluated according to a set of criteria. Besides, the information provided by group members is expressed as *IVIF* decision matrices, where each element is characterized by an interval-valued intuitionistic fuzzy number. This approach first normalizes all cost attributes into benefit attributes to avoid a wrong decision result. Thereafter, it employs a *continuous interval argument OWA (C-OWA) operator* (Yager 1988) to transform *IVIF* number samples into single-valued samples. During the transformation, to guarantee that the preference information of group members is aggregated objectively, a *BUM function* (Yager 2004) is provided to each group member according to his/her risk attitudes. The BUM (*balanced incomplete unbalanced linguistic preference relations and their applications*) function is a mathematical tool to aggregate linguistic preference information in a group decision-making context. The BUM function can be used to calculate a collective preference order from a set of individual preference orders, each of which may be uncertain, incomplete, or unbalanced.

Remark By comparing the two mentioned methods, the method proposed by Liu et al. (2014) better helps to resolve the drawback of the *CMALGDM* problems that contain uncertainties regarding preference information.

b. Consensus-achieving processes in LS-GDM: There are several approaches proposed for this method:

Approach 1 (Rodríguez et al. 2012): The main idea is to model different types of preference information together with the *group's attitude* toward achieving agreements. Preference information can be expressed in different domains, such as numerical, interval-valued, and linguistic domains. This approach is related to the group's attitude, and a required consensus level can be obtained according to the attitude of group members. Two types of group attitude are taken into account: *optimistic attitude* and *pessimistic attitude*. Regarding *optimistic attitude*, achieving an agreement is more important for group members than their own preferences. Therefore, more importance is given to positions in the group with higher agreement. *Pessimistic attitude* shows a contrast tendency, where group members put a higher importance on their own preferences. Therefore, positions in the group with lower agreement are given more importance. In this approach, an *attitude-OWA operator* (an extension of the OWA operator) can be used to integrate the attitude of group members in the consensus-achieving process. We refer to Rodríguez et al. (2012) for further details.

Approach 2 (Palomares et al. 2014a; Quesada et al. 2015; Dong et al. 2016): The goal of this approach is to deal with group decisions where some group members/subgroups are not willing to adapt their preferences to achieve a consensus. To address this goal, this approach tries to detect and manage non-cooperating users/subgroups to speed up the consensus-achieving process.

Approach 3 (Xu et al. 2015): This approach extends *Approach 2* by additionally determining *minority opinions* that hinder the consensus-achieving process, besides *non-cooperative behaviors*. *Minority opinions* are referred to as views or ideas held by a small number of individuals within a group that differ from the opinions given by the majority of the group. Minority opinions should be considered, especially in emergency group decision-making scenarios where high-quality decision-making results are required to avoid a wrong decision that causes incalculable losses. An example of minority opinions in an emergency group decision-making scenario is described as follows. In emergency evacuation planning, there may be a minority opinion on the best evacuation route or strategy. For instance, one group member may suggest a different route they believe would be safer or more efficient. By considering the minority opinion, the group can evaluate potential alternatives and make the best decision for the safety of the individuals involved. In summary, in emergency scenarios, the views of all group members should be fully considered, predominantly minority opinions, and the interests of all parties should be well-balanced.

Approach 4 (Wu and Xu 2018): The main idea is to construct an interactive consensus model where the clusters are changed whenever group members modify their preferences throughout the consensus-achieving process. Furthermore, with the assistance of the decision support system, the clusters are recognized as virtual clusters. Changes in the clusters do not affect the preference adaptations of group members.

Approach 5 (Tang et al. 2021; Tang and Liao 2021; Gou et al. 2018): The main idea is that the consensus-achieving process is guided and supervised by a moderator or the representatives of subgroups.

Remark *Approaches 1 and 2* present consensus models for non-cooperative behaviors, which show two limitations. First, they do not consider the *emergencies* when the decision must be made promptly. Even non-cooperative behaviors should be taken into account to guarantee high-quality decisions. In this context, it is more crucial to ensure the timeliness of decision-making (Xu et al. 2015). Second, it fails to provide mechanisms to deal with *minority opinions* that hinder the consensus-achieving process. *Approach 3* can resolve the mentioned drawbacks. In particular, through an illustrative example regarding an emergency situation in the coal mine, this approach has been proven to be feasible and efficient for managing the mentioned issues in large-group emergency decision-making problems (Xu et al. 2015). However, these three approaches focus on detecting and managing non-cooperative behaviors by updating the clusters' weight. It is usually assumed that the obtained clusters do not change. However, when group members' preferences are modified, this is generally not the case anymore. *Approach 4* has been presented to effectively solve this issue. Finally, *Approach 5* allows the consensus-achieving process to be done in a different fashion compared to the previously mentioned approaches, which achieves higher efficiency. Instead of updating the weighted average of group members' preferences in subgroups/clusters, *Approach 5* applies a more realistic mechanism where a moderator communicates with the representatives of subgroups, which accelerates the consensus-achieving process.

c. LS-GDM support systems: In LS-GDM, users tend to participate in the decision process and express their opinions at different points of time and places. Therefore, the main idea of the related consensus-achieving approaches is to develop effective decision-support systems facilitating users' participation in LS-GDM. Turoff et al. (2002) propose a new type of information/communication system that supports the participation of large groups of users in social decision-making. This approach uses the concept of social decision-support systems, which is regarded as an LS-GDM support system in the social choice process. This system aims to produce, integrate, and synthesize diverse views in such a way that allows all users to respect and understand the differences caused by the diverse values and interests of the contributing population. Besides, this system supports a movement towards consensus and makes decisions on *societal-scale issues*. These issues can be particularly challenging in LS-GDM, as they often involve complex trade-offs and conflicting interests. For instance, group decision-making on public health issues, such as vaccination programs or pandemic response strategies, can impact large populations and require consideration of a wide range of factors, including public opinion, scientific evidence, and resource availability. In the same research line, Carvalho et al. (2008) develop a system so-called LaSca that supports group decisions of three types of users: *creator, participant,* or *moderator*. A creator is able to formulate a new problem. A participant is allowed to provide opinions on the problem formulated by the creator. Finally, a moderator can receive and summarize the opinions provided by the participants. Palomares et al. (2014b) develop a map-based graphical monitoring tool, so-called Mentor, that supports group members in analyzing information about the status of LS-GDM problems during their resolution. This tool facilitates the achievement of important information about various features, such as detecting agreement/disagreement positions within the group, the adaptations of group members' preferences, and the closeness level between group members' preferences achieved during the consensus-achieving process.

Remark The mentioned tools/systems can be integrated into an existing group decision-support system to obtain a new design and a highly interpretable group decision-support system that better supports asynchronous group decision-making processes (Palomares et al. 2014b).

5 Consensus models for group recommender systems

Basic concepts, as well as consensus models used in group decision-making, can be basically exploited to generate related consensus models in group recommender systems (Castro et al. 2018; Yera et al. 2018). However, the application of these consensus models to group recommender systems has yet to be studied sufficiently. The current literature shows two main directions of this application, clearly shown in consensus models based on fuzzy preference relations and minimum cost. We have seen that *fuzzy preference relations* (Cabrerizo et al. 2017b; Herrera-Viedma et al. 2002; Palomeres et al. 2011) can be used to develop a consensus approach in a group recommender system that overcomes the drawback of the basic aggregation strategies (Castro et al. 2018; Gallardo et al. 2015). *A minimum cost consensus model* in a group recommender system (Yera et al. 2018) can be generated based on a corresponding consensus model under OWA operators (Zhang et al. 2011).

Besides, the focus of consensus model-related work in group decision-making is quite different from this in group recommender systems research. While most consensus models in group decision-making attempt to compute soft consensus measures, related models in group recommender systems focus on improving the basic aggregation mechanisms and achieving group recommendations with a high agreement level. As mentioned in Sect. 3.1, to generate a group recommendation, the information of individual group members is merged using aggregation strategies. Some systems aggregate group members' preferences (Ortega et al. 2016), whereas others aggregate individual recommendations (Ardissono et al. 2003). Recent studies have pointed out that it is necessary to develop recommendation approaches beyond the basic aggregation approaches since solely applying these aggregation mechanisms does not guarantee a high agreement level among group members regarding the group recommendations (Castro et al. 2018; Gallardo et al. 2015; Masthoff and Delić 2022; Yera et al. 2018). On the other hand, these mechanisms do not consider essential aspects regarding group recommendation scenarios, such as overlapping experiences among group members (Castro et al. 2018) or conflicts about recommendations within the group (Yera et al. 2018). Ignoring the mentioned aspects could lead to biased recommendations and, as a result, dismissing group members' satisfaction with group recommendations (Boulkrinat et al. 2015; Castro et al. 2018). This section presents various consensus approaches to aggregating individual user models, overcoming the mentioned limitations and achieve a high consensus level on group recommendations (see Sect. 5.1). We present these approaches according to the applied techniques such as *fuzzy preference relations* (Gallardo et al. 2015), *opinion dynamics* (Castro et al. 2018), *range voting technique* (Boulkrinat et al. 2015), *minimum cost consensus model* (Yera et al. 2018), *statistical dispersion* (Salamó et al. 2012), *individual content* (Borowik et al. 2015; Cerquides et al. 2007; Masthoff and Gatt 2006), and *negotiation method* (Choudhary et al. 2020; Nguyen and Ricci 2017b; Schiaffino et al. 2020; Bahari Sojahrood et al. 2023; Villavicencio et al. 2019).

Although the above-mentioned approaches have already considered some factors beyond group members' preferences, other social interactions (e.g., social relationships, expertise, and preference dissimilarity between group members (Gartrell et al. 2010)) need to be further investigated. Ignoring these factors can result in sub-optimal group recommendations. We have found in the literature another type of group recommender systems exploiting interactive and conversational approaches to facilitate the group decision-making process. These systems compose of new consensus strategies that integrate individual and social interactions in the group recommendation process (Contreras et al. 2021; Emamgholizadeh 2022; Gartrell et al. 2010).

In addition to algorithmic-oriented consensus methods, further approaches based on explanations and visualization methods have also been proposed for accelerating the consensus-achieving processes. These approaches help to intuitively describe the current consensus state of the group or conflicts among group members (Najafian and Tintarev 2018; Quijano-Sánchez et al. 2017; Tran et al. 2019). Moreover, they provide group members with solutions/hints on how to adapt their preferences until achieving an agreement.

Based on the discussed aspects, in the following sections, we present consensus approaches categorized into three groups: consensus approaches to improving traditional aggregation strategies (Sect. 5.1), consensus approaches considering social relationship interactions (Sect. 5.2), and consensus approaches based on explanation and visualization methods (Sect. 5.3). It might be observed unequal distributions of consensus approaches across the sections. Particularly, Sect. 5.1 has more consensus approaches presented compared to Sects. 5.2 and 5.3. The reason lies in the predominant number of consensus approaches in the existing literature that attempt to improve traditional aggregation strategies. Another note for this section is that, due to the high number and solid content of the presented approaches, we will provide only the main idea of the consensus approaches and refer readers to the related studies for further details. Besides, similar to Sect. 4, we also add a *short remark* to further discuss the strengths and drawbacks of the presented approaches. Furthermore, to provide readers with better guidance for using the existing consensus approaches, we discuss their application scenarios as well as their main idea (see also Table 3). A summary of the consensus approaches for group recommender systems can be found in Table 4.

5.1 Consensus approaches to improving the basic aggregation strategies

5.1.1 Fuzzy preference relations

When to apply? The consensus approach based on fuzzy preference relations can be applied in any group decision where uncertainty or imprecision exists in the decision problem. This approach can also support situations where the preferences of group members for a list of selected items can be specified, translated, or aggregated using fuzzy preference relations (Palomares and Martinez 2014). For instance, in a tourism group recommender system, fuzzy preference relations can be used to aggregate the preferences of different group members (see also related discussions in Sect. 4.1.1). Each member's preference for a travel destination can be represented using a fuzzy preference relation. These relations are merged to generate a group preference for different travel destinations.

Basic concepts The main idea is to translate the recommendations of individual group members to fuzzy preference relations before merging them to calculate the group's agreement level.

A group recommender system based on this idea is proposed by Gallardo et al. (2015), integrating a group recommendation process that considers an added value for reaching a certain agreement level concerning group recommendations. In the recommendation phase, necessary computations are done to generate a set of predictions (recommendations) for each group member. The predictions are ordered from the best to the worst items. Consequently, a preference order is created for each group member over the top-n items that have been predicted for him/her. The consensus phase is then activated to obtain a collective list of predictions for the group with a high consensus degree among individual predictions. At the beginning of this phase, individual recommendations for group members are translated to *fuzzy preference relations* since a consensus model with preference relations is utilized. Thereafter, a consensus-achieving process is performed to gradually bring group members' preferences closer to each other until a high level of agreement is achieved. This consensus model integrates a mechanism that automatically updates the preferences of group members. At each round of the consensus-achieving process, this model is performed in three phases (as mentioned in Sect. 3.3) until a consensus is achieved. In the first phase, fuzzy preference relations of group members are gathered and utilized to calculate the agreement level in the group. The calculated consensus degree is checked in the second phase to determine if it indicates enough agreement. If the consensus degree is not lower than a pre-defined consensus threshold θ, then a consensus among group members has been

Table 3 Application scenarios and main ideas of consensus approaches for group recommender systems

Consensus approach	Application scenarios	Main ideas
Fuzzy preference relations (Sect. 5.1.1)	Group decision-making processes involve multiple attributes; uncertain in the decision problem; group members' preferences are aggregated using fuzzy preference relations	Translate individual group members' recommendations to fuzzy preference relations before merging them
Opinion dynamics (Sect. 5.1.2)	Lack consensus among group members; group members' preferences change over time; group members have different expertise levels	Consider relationships between group members' preferences
Range voting technique (Sect. 5.1.3)	Group members can linguistically express the relations between their choices	Resolve drawbacks of the existing voting techniques
Minimum cost consensus (Sect. 5.1.4)	Group members have conflicting preferences	Minimize the cost of modifying group members' preferences
Statistical dispersion (Sect. 5.1.5)	Group members' preferences are diverse	Identify items with a high degree of dispersion and variability in their ratings; the consensus-achieving process is performed with two strategies—dispersion and probability theory
Individual content (Sect. 5.1.6)	High degree of variability in group members' preferences	Measure individual satisfaction of group members w.r.t individual content strategies
Negotiation method (Sect. 5.1.7)	There are conflicting and diverse group members' preferences	Integrate a negotiation method to generate group recommendations that satisfy group members
Social relationship interactions (Sect. 5.2)	Social relationships and interactions between group members play an important role	Consider social interactions among group members
Consensus explanations and visualization methods (Sect. 5.3)	Provide consensus explanations that intuitively describe the current consensus status of group members	Develop explanations that show and resolve group members' conflicts

Table 4 Summary of consensus approaches for group recommender systems

Consensus approach		Related work
Improving the basis aggregation strategies (Sect. 5.1)	Fuzzy preference relations	Gallardo et al. (2015)
	Opinion dynamics	Castro et al. (2018)
	Range voting technique	Boulkrinat et al. (2015)
	Minimum cost consensus model	Yera et al. (2018)
	Statistical dispersion	Salamó et al. (2012)
	Individual content	Salamó et al. (2012), Cerquides et al. (2007), Borowik et al. (2015), Masthoff and Gatt (2006)
	Negotiation methods	Bahari Sojahrood et al. (2023), Choudhary et al. (2020), Nguyen and Ricci (2017b), Schiaffino et al. (2020), Villavicencio et al. (2019)
Considering social relationship interactions (Sect. 5.2)	Developing conversational group recommender systems taking into account social interactions of group members	Contreras et al. (2015), Contreras et al. (2021), Gartrell et al. (2010), Nguyen and Ricci (2017b)
Consensus explanations and visualization (Sect. 5.3)	Showing group members' conflicts	Alonso et al. (2007), Mahyar et al. (2017), Palomares et al. (2014b)
	Resolving group members' conflicts	Najafian and Tintarev (2018), Quijano-Sánchez et al. (2017), Tran et al. (2019)

reached, and the consensus-achieving process completes. Otherwise, preference values need to be updated. An additional parameter—*Maxround* is used to limit the number of consensus rounds. In the last phase, group members' preferences farthest from the consensus are identified. Corresponding preference adaptations are performed to increase consensus in the following rounds. Once group members' preferences have been updated, another consensus round is activated. As soon as the consensus has been reached, the collective preference P_c reflecting a high level of agreement is used to deliver a list of agreed items to the group. Gallardo et al. (2015) deployed a user study in the movie domain to evaluate the approach. The experimental results show that applying the proposed consensus in a group recommender system helps to improve the satisfaction of group members compared to the baseline group recommendation techniques (i.e., k-nearest neighbors algorithm and least misery aggregation strategy).

5.1.2 Opinion dynamics

When to apply? The consensus approach based on opinion dynamics can be applied in a group recommender system supporting the following group decisions:

- When there is a lack of consensus among group members: If the individual preferences of group members are widely different and there is no clear preference for a particular item, the consensus model based on opinion dynamics can help to bring the group members to a shared preference by allowing them to interact and influence each other (Castro et al. 2018).
- When the preferences of group members are expected to change over time: In some situations, individual group members' preferences may be influenced by new information or by the opinions of others (Castro et al. 2018; Urena et al. 2019).
- When group members have different expertise/knowledge levels: In some cases, certain group members may have more expertise or knowledge on a particular topic than others (Nguyen 2017).

Basic concepts The main idea is to consider the relationships between group members' preferences for generating group recommendations with a high agreement of individual group members.

Following the mentioned idea, Castro et al. (2018) propose a framework for group recommendation based on opinion dynamics based on *opinion dynamics* (Dong et al. 2016) with consensus (*GROD*) and the extension of *DeGroot's model* (Degroot 1974). *Opinion dynamics models* are used to describe particular aspects of the social behavior of group members and model how group members' opinions evolve over time (Castro et al. 2018). The model of DeGroot assumes that users change their opinions according to a social influence model, in which each user considers another user's opinion with a certain weight. Based on these concepts, the proposed framework applies a flexible process to produce a group value, given that it is driven by the matrix of weights between group members. The framework consists of two models: *Pre-GROD* and *GROD*. *Pre-GROD* extends to group recommender systems and considers relationships between group members' preferences in the recommendation phase. This model generates a group recommendation in four steps: (1) computing individual group members' predictions; (2) calculating the relationships between group members' preferences; (3) predicting the group rating for each item using *DeGroot's model*; and (4) recommending items with high predicted values. The *Pre-GROD* model does not ensure consensus and, therefore, yields a group recommendation that does not satisfy all group members. To address this issue, the *GROD* model is proposed that extends the Pre-GROD model by adding a sub-step to *step 2* to ensure the conditions to calculate consensus recommendations. In this substep, a *relation matrix* is analyzed and, if needed, is modified to ensure consensus. To evaluate the mentioned model, Movielens datasets (for single users) were used and then synthesized to create group-related datasets. The experimental results show that the proposed framework improves the performance of the preference aggregation strategy compared to the baseline (the average aggregation strategy) since it considers the relationships between group members' preferences when generating group recommendations. Moreover, the framework ensures consensus in recommendations.

5.1.3 Range voting technique

When to apply? The consensus model based on the range voting technique can be applied in a group recommender system that supports situations where group members are allowed to linguistically evaluate all candidate options using *the relations* between their choices. For instance, *"I strongly prefer item A over the two remaining ones B and C for which, I have a slight preference between them"*.

Basic concepts The main idea is to resolve drawbacks of the existing voting techniques such as *Approval voting, Plurality voting,* and *Utilitarian voting* (Felfernig et al. 2018a; Masthoff 2011) where the preferences of some group members are ignored. Although other voting techniques (such as *Condorcet* and *Borda count* (Masthoff 2011)) can solve the mentioned drawback, the *preference intensity* is simply missing in these techniques.

Boulkrinat et al. (2015) present a consensual recommendation approach based on the *range voting technique*. This technique builds up a *consensus sequence of tourism attractions* that will be recommended to the group as a joint decision. Range voting allows group members to linguistically evaluate all candidate options, where they can express *the relation* between their choices (see the example above). This relation shows not only which option a group member may prefer over another but also how much he/she likes an item through the intensity of each of his/her preferences. This way, range voting improves recommendation outcomes since it captures the first choice of group members and the relative deviation between different choices from a preferential point of view. Besides, to achieve a satisfying choice for all group members, the authors consider the consensual sequence, in which they alter each time only one item from its initial position with another and keep the rest unchanged. By doing so, group satisfaction might be captured better, while not deviating too much from the initial consensual sequence. This re-ordering process continues until optimal group satisfaction is reached. The optimal group satisfaction is determined through a *gain value* that measures *the total number of satisfied options for all the group members*. To evaluate the performance of the approach (in terms of group satisfaction), the authors use tourism datasets from *TripAdvisor*[8] and form groups artificially. Thereafter, they compare the gain values given by the proposed approach with these given by a baseline approach (*least misery* strategy). The experimental results show a better performance in terms of gain values, meaning that the range voting technique achieves a higher group satisfaction level than the baseline approach.

5.1.4 Minimum cost consensus

When to apply? The consensus model based on minimum cost consensus can be applied to group decisions where group members have conflicting preferences.

Basic concepts. The main idea is to minimize the cost of modifying group members' preferences.

Yera et al. (2018) propose a *minimum cost consensus* approach that reaches a higher consensus and acceptance regarding the final group recommendation. The general scheme of this approach consists of three phases: (*phase 1*) individual recommendation generation, (*phase 2*) Borda count-based ranking, and (*phase 3*) minimum cost consensus analysis. In the first phase, a collaborative filtering recommendation approach is applied to generate the recommendations for individual group members. In the second phase, to reduce the computational cost, the Borda count-based ranking strategy is used to decrease the possible set of recommended items used in the consensus phase (i.e., only the top-k ranked common items will be sent to the consensus phase). Finally, in the last phase, a minimum cost consensus model is applied to the top-k common items achieved in *phase 2*. This phase receives the prediction values of individual group members and adjusts the group recommendation to reach a consensus. As the final output, the model recommends the group items that receive the highest agreement of all group members. The main idea of the minimum cost consensus model is to *minimize costs associated with modifying group members' preferences to reach a consensus*. Such minimum cost can be obtained by solving a linear programming model (Zhang et al. 2011). This cost is computed independently for each item i, considering the four following assumptions for translating a consensus model notation into a group recommender system scenario: (1) each user preference on an item i is the opinion of a group member u on i; (2) the cost of modifying the preferences of u is always 1; (3) given n number of group members, a group member's weight is always 1/n; and (4) the maximum possible distance between collective preference (representing group preference) and individual group members' preferences should be equal to a pre-defined value. A performance evaluation was conducted with movie datasets. The performance values show that the consensus model could lead to the improvement of the recommendation performance.

5.1.5 Statistical dispersion

When to apply? The consensus model based on statistical dispersion can be applied in a group recommender system supporting situations with diverse opinions or preferences within the group.

[8] https://www.tripadvisor.com.

Basic concepts The main idea is to identify items with a high degree of dispersion or variability in the ratings/preferences among group members. In this context, a consensus-achieve process is proposed with two strategies based on the measurements of *dispersion* used in statistics and probability theory (Salamó et al. 2012). The first dispersion strategy, called *mean*, indicates the mean satisfaction of the group for a specific item. This measure is defined as the *average of the satisfaction of group members according to their preferences*. It helps to derive a central tendency of the preference space. Based on this measure, the so-called *deviation* measure is calculated to specify the variability or diversity from the *mean*. A low deviation indicates that group members' preferences are close to the mean. In contrast, a high deviation shows that group members' preferences are spread over a large range of values.

The second dispersion strategy is the so-called *purity* that measures the percentage of positive preferences among the whole set of preferences made by the group. A *purity* value = 1 denotes that all group members' preferences are satisfied. In contrast, a *purity* value = 0 means that none of the group members' preferences are satisfied.

5.1.6 Individual content

When to apply? The consensus model based on individual content can be applied in a group recommender system that supports situations with a high degree of variability in the preferences of group members.

Basic concepts The main idea is to measure the satisfaction of individual group members with a specific item based on the following individual content strategies: *completeness, logical sufficiency,* and *group sufficiency* (Salamó et al. 2012).

The *completeness* measure has been previously used in negotiation scenarios (e.g., in auctions scenarios (Cerquides et al. 2007)) where the provider and buyer want to reach an agreement for the best offer. Instead of performing negotiations between two individuals, like in auction scenarios, group recommendation scenarios need negotiations involving more than two individuals. The objective of the completeness measure is to support high satisfaction scores while penalizing significant differences among group members. This measure is computed based on the satisfaction of group members. It also considers a *weighting factor* that allows putting a higher focus on some group members than others. For instance, experts in software requirements engineering scenarios can have a higher weight than other stakeholders. The completeness values are normalized to the values $\in [0, 1]$.

The *logical sufficiency* measure (in short, the *ls* measure) is a standard likelihood ratio statistic, which has been used to measure the rule quality of *rule induction systems* (Borowik et al. 2015). The *ls* degree of an item for a user is defined as the ratio of the satisfied preferences of the user to the user's preferences that are not satisfied. The larger the *ls* value, the higher the user's satisfaction with an item. The *ls* value of an item for a group is defined as the sum of the individual *ls* values of group members divided by the total number of preferences in the group.

In inductive rule learning algorithms, the *ls* measure causes the development of a new measure—*lscontent*. This measure estimates the local sufficiency measure with a Laplace correction that penalizes items with low-level satisfaction for group members. There are no differences between *ls* and *lscontent* when we evaluate the degree of logical sufficiency of an item in relation to an individual group member. However, *lscontent* might help to reach a consensus when we apply the degree of *logical sufficiency* to describe a *group sufficiency*. The *group sufficiency* (in short, the *gs*) measures the satisfaction of a group member in relation to the satisfied preferences and unsatisfied preferences of the other group members. The underlying idea of this strategy originates from the *emotional contagion* concept (Masthoff and Gatt 2006) where the satisfaction of an individual group member tends to depend on that of other group members.

5.1.7 Negotiation method

When to apply? The consensus model based on negotiation methods can be applied in a group recommender system with conflicting or diverse preferences among group members. This approach involves negotiating and compromising to reach a consensus recommendation that satisfies the preferences of as many group members as possible.

Basic concepts The negotiation method is expected to generate recommendations that satisfy group members more uniformly than other approaches such as voting or auction-biding (Villavicencio et al. 2019). This method can be integrated into group recommender systems to find consensus and create group recommendations with a high satisfaction level for all group members (Gross 2019).

In the literature, we have observed a common approach where a group recommender system is built based on a *multi-agent solution - MAS* and *a negotiation method* (Choudhary et al. 2020; Schiaffino et al. 2020; Bahari Sojahrood et al. 2023; Villavicencio et al. 2019). There also exist a few earlier studies applying only a MAS in group recommender systems, especially in the tourism domain (Sebastiá et al. 2010; Sebastia et al. 2011). However, these approaches heavily rely on traditional aggregation strategies (either for aggregating user preferences or group members' recommendations (Felfernig et al. 2018a)) and do not integrate a negotiation mechanism, which consequently triggers unsatisfying recommendation outcomes. A study proposed by Nguyen and Ricci (2017b) introduce a group recommender system for points of interest (POI) that allows group members to repeatedly express and revise their preferences during the decision-making process through a chat-based application. Although this study applies improvements in preference elicitation and revision for increasing the quality of recommendation outcomes, group members need more effort to discuss the options and then vote for them.

Approaches proposed more recently that integrate MAS with the negotiation method can resolve the mentioned issues. For instance, Villavicencio et al. (2019) and Schiaffino et al. (2020) develop a group recommender system, so-called *MAGReS (Multi-Agent Group Recommender System)*, in which a personal agent represents a group member, saves his/her preferences, and acts on his/her behalf when making item proposals to other agents and looking for agreements. These agreements are achieved by the agents through a cooperative negotiation process. The authors select a multilateral negotiation method known as *Monotonic Concession Protocol (MCP)* that closely describes how human negotiation works (Endriss 2006). The main idea of *MCP* is to ensure two aspects: (1) any negotiation process following the protocol will eventually terminate and (2) at least one agent can concede until an agreement has been obtained. MCP can be performed in two steps: *step 1*—each agent makes an initial proposal according to its initial proposal strategy (e.g., selecting a top-ranked item with the highest utility value), and *step 2*—the initial proposals of all the agents are exchanged to analyze if an *agreement* over one of the proposals can be reached. The notion of *agreement* is defined based on the *Multilateral Agreement Criterion* that is described formally as follows: An agreement is reached if and only if there exists an agent ($ag_i \in A$) whose proposal x_i is accepted by every other agent $ag_k \in A$. The proposal accepted by each agent $ag_k \in A$ is determined by the Proposal Acceptance (PrA) strategy used by that agent. This strategy proposes a flexible way to define acceptance, which includes three levels: *strict, relax,* and *next*. For further details of the PrA strategy, we refer to Villavicencio et al. (2019). If an agreement is reached, the proposal satisfies all the agents. Otherwise, one (or more) agents need(s) to concede. A concession means that an agent seeks an inferior proposal (in terms of its utility), hoping to reach an agreement. The concession can be performed using different strategies [for further details, see Villavicencio et al. (2019)]. If none of the agents can concede, the process ends without an agreement. To evaluate the performance of *MAGReS*, single-user datasets in the movie and POI domains are used to synthesize group datasets. Two baseline approaches (i.e., preference aggregation and recommendation aggregation) are selected. The performance of *MAGReS* is evaluated based on three dimensions: *group satisfaction* (the satisfaction of the group w.r.t the recommended item), *group members' satisfaction dispersion* (how uniformly group members are satisfied by either a single item or a recommendation), and fairness (the percentage of group members satisfied by the recommendation). The experimental results show that using the proposed negotiation method (instead of baseline techniques) can significantly improve the quality of group recommendations w.r.t the mentioned dimensions. However, *MAGReS* faces one limitation where the social factors between group members (such as friendships, trust, and common tastes) are ignored. Meanwhile, these factors are assumed to affect group recommendation outcomes and, therefore, can change the resulting average satisfaction of some group members (Masthoff 2011).

To overcome the mentioned issue, Choudhary et al. (2020) propose a multi-agent negotiation protocol for group recommendation that extends the *MAGReS* protocol (Schiaffino et al. 2020; Villavicencio et al. 2019)) by further considering the *trust* factor. This protocol allows agents to accept or discard part of the offer based on trust and distrust among users, which gives more agility to the negotiation process. Trust and distrust factors help to obtain more satisfactory bargaining outcomes (Liu et al. 2016). Besides, according to the *Influential Theory*, a higher level of trust/distrust among two users can lead to an agreement/disagreement on some issues (Wang et al. 2013). In other words, a higher level of trust (or a lower level of distrust) yields an agreement. Trust and distrust can be represented by *seven standard triangular fuzzy sets* (Girdhar et al. 2019; Kant 2013). An example of seven fuzzy sets for trust are the following: *zero trust (ZT), very low trust (VLT), low trust (LT), medium trust (MT), high trust (HT), very high trust (VHT),* and *full trust (FT)*. Similarly, seven fuzzy sets for distrust are *zero distrust (ZD), very low distrust (VLD), low distrust (LD), medium distrust (MD), high distrust (HD), very high distrust (VHD),* and *full distrust (FD)*.

Based on the mentioned theory, Choudhary et al. (2020) introduce a *fuzzy trust/distrust-based negotiation model* for group recommendation. This model is organized along the following steps:

- *Step 1*: An agent (representing a user or a group member) makes an initial proposal for its favorite item according to the *Zeuthen strategy* (Villavicencio et al. 2019) (i.e., selecting an item with the highest utility value).
- *Step 2*: The fuzzy trust and distrust of all remaining agents on the active agent are computed. The trust/distrust score for a user u_i to another user u_j is denoted as $TD_{u_i,u_j} = (trust_{tag}, distrust_{tag})$, where $trust_{tag}$ and $distrust_{tag}$ represent the linguistic labels for trust and distrust, respectively. These scores are exploited to compare the trust and distrust labels given by one user to another in the system. They can be computed based on the fuzzy computational model proposed by Kant (2013), taking into account two factors: *similarity* and *knowledge*. The *similarity-based trust and distrust values* between two users are calculated according to their liking or disliking of a common item. The *knowledge-based trust and distrust values* between two users are calculated based on reciprocity and experience between users. See further details of calculating these values in Choudhary et al. (2020).
- *Step 3*: If all the agents have fuzzy trust values as *FT, VHT, HT* and distrust values as *ZD, LD, VLD* then the negotiation process finishes with an agreement on the proposed offer. Otherwise, the proposed offer is rejected.
- *Step 4*: There are two possibilities:
  - If the proposed offer is rejected and all the offers have not been proposed yet, then the next agent with lower *Willingness to Risk Conflict (WRC) value* will be an active agent. A utility function, which is associated with ratings provided by users to the items, is used for each agent in the group. The ratings can be actual ratings or predicted ones. If a user rated an item, its actual rating is considered as its utility. If a user did not rate an item, the ratings could be computed by a single-user recommendation technique (Li et al. 2018). So, we select an active agent by applying the *Zeuthen strategy* (Villavicencio et al. 2019). Each agent in a group computes the WRC value [see the calculation formula in Choudhary et al. (2020)] and selects an agent with the lowest WRC value as an active agent.
  - If the deadline (the maximum time for the negotion process) is reached and there is no agreement on any of the items, the negotiation process ends without an agreement.

At the end of the negotiation process, the proposed offer with an agreement is recommended to all the group members.

To investigate the performance of the proposed negotiation model, the authors test it with different real-world datasets such as MovieLens,[9] Epinions,[10] and Book-Crossings[11] and compare with baseline techniques such as Average Strategy, Least Misery Strategy, and Most Pleasure Strategy (Felfernig et al. 2018a; Masthoff 2011).

[9] https://grouplens.org/datasets/movielens/100k/.

[10] https://snap.stanford.edu/data/soc-sign-epinions.html.

[11] https://www2.informatik.uni-freiburg.de/~cziegler/BX/.

The experimental results show that the proposed negotiation model shows a higher level of effectiveness of a group recommendation compared to the baseline ones. The effectiveness of a group recommendation in this work can be measured in terms of group satisfaction that is the average satisfaction of its group members.

Remark Although experimental results show that the mentioned consensus approaches (presented in Sects. 5.1.1–5.1.7) help to improve recommendation outcomes in different aspects, we believe that these evaluations are not sufficient due to the following reasons. First, no real group-related datasets have been used to evaluate the consensus models. All of the group datasets used in these consensus approaches are synthesized from the single-user datasets. Second, for some approaches [e.g., Choudhary et al. (2020), Castro et al. (2018)], weak baseline techniques (e.g., *Average* strategy) are selected, even though a better baseline could have been used instead (e.g., using *Least Misery* instead of *Average*). Average can be a bad strategy for polarity groups where the preferences of group members are distributed on both sides of a spectrum. In this context, this strategy forces group members to give up their preferences to achieve an outcome that no one really likes. Third, although experimental results show that the mentioned approaches present a higher quality of group satisfaction, this aspect has not been proven sufficiently since the feedback was done after experiencing the recommendation approaches (Boulkrinat et al. 2015; Yera et al. 2018). Finally, the proposed approaches have been tested only in a few item domains (mainly in the movie and tourism domains), which limits generalization.

5.2 Consensus approaches considering social relationship interactions

When to apply? The consensus model considering social relationships can be applied in a group recommender system where social relationships and interactions between group members are important factors in decision-making. This approach recognizes that group members are not independent entities and that social relationships and interactions can influence their preferences and decision-making.

Basic concepts While most of the previously mentioned approaches focus on the content interests of group members and ignore the social interactions among them, the consensus approaches in this section take this aspect into account to increase the group recommendation performance.

Gartrell et al. (2010) propose a group recommender system with group descriptors that examine the impacts of different social interactions (such as *social relationships, expertise,* and *dissimilarity*) on group decisions. A *social descriptor* measures the *social relationship strength* of a group. This strength between two group members can be quantified using a *five-level scale* (1: weakest, 5: strongest). For instance, the social strength of a family that consists of a husband and wife is usually perfectly suitable for level 5 because they meet each other almost daily. Meanwhile, the social strength of a faculty member and his Ph.D. student may fit level 2 since they have regular meetings twice a week. The two-member social measure is extended to measure the social relationship strength of a group with more than two users. This measure considers the group size and the strength of each pair of group members. *Expertise descriptor* measures the relative expertise of two individual group members. In general, the opinions of experts may be weighted more heavily than those of other group members. The expertise of a group member is also measured using a five-level scale. It can also be identified based on the number of items a group member has consumed. The higher the number of consumed items, the higher the expertise level. The *Dissimilarity descriptor* measures the preference disagreement between two group members. Intuitively, the closer the preference for an item between two group members, the lower the disagreement between them. To describe the preference difference of a group, *average pairwise dissimilarity* is used to calculate the average of the differences between all pairs of group members. In this context, a *heuristic-based group consensus function* is presented. This function incorporates all the factors mentioned above to generate the final group rating for a given group and a given item. Gartrell et al. (2010) observe that when the social relationship strength is strong and tight, the final decision for a group tends to reflect the maximum satisfaction of group members. Otherwise, the final decision follows average satisfaction or minimum misery strategies. In order to boost the quality of group decision outcomes and increase the satisfaction of all group members, all three descriptors are combined into a heuristic group consensus function using the most common group strategies [see Equation 8 in Gartrell et al. (2010)]. In order to evaluate the performance of the proposed group recommender system, the authors conducted a user study in the movie domain with 30 individual participants who were then formed into 10 different groups. The experimental results show that the proposed group consensus function significantly improves the overall prediction quality compared to traditional aggregation strategies (e.g., *average, max,* and *min*).

With a similar idea as (Gartrell et al. 2010), Nguyen and Ricci (2017b) develop a chat-based group recommendation environment that takes into account the interactions of group members with the items. In this system, group members do not interact directly but provide feedback on the items other users proposed to the whole group. The amount of feedback allows the system to infer who is the most active user in the group. *An active user is a group member who highly interacts with items over the session.* This interaction can happen by providing ratings or preferences over the items and is not necessarily a collaboration with other users in the group. Although this work embraces interactions in the group recommendation process, it shows some issues, such as a lack of the consideration of implicit feedback on items or the limited definition of an active user that might not be enough to recognize the role of the leader and other group members.

To resolve the mentioned issues, Contreras et al. (2021) propose a collaborative model considering social interactions taking place in a *conversational group recommender system* (Jannach et al. 2021). This model allows the group recommender system to implicitly infer the different roles within the group, namely, collaborative and leader user(s). Different from Nguyen and Ricci (2017b), a leader user in this approach is defined as an influencer of the group who has been providing the group with suggestions, of which some or all have been viewed and stacked by other group members. Contreras et al. (2021) also build a group conversational recommender system based on *gCOACH* (Contreras et al. 2015). This web-based platform provides an environment where group members can interact on a one-to-one basis thanks to the included interaction modalities. These modalities collect implicit feedback on the collaboration and leadership of the users in the group. Besides, *gCOACH* refines the choices of group members by providing feedback and making suggestions to a specific group member. However, different form *gCOACH*, the conversational group recommender system proposed by Contreras et al. (2021) includes social interactions in the group modeling consensus strategy and therefore reshapes the group recommendations based on group interactions. To model social interactions, a model with two components is developed: *individual models* storing individual group members' preferences and *collaborative models* representing the collaborative user model of group members. Each collaborative user model shows a group member's social interactions with the remaining group members and how these interactions have been viewed and accepted by each individual user. Based on this proposed model, new collaborative-consensus strategies are developed, integrating *collaboration models* into the traditional aggregation strategies (e.g., *collaborative mean, collaborative completeness, collaborative multiplicative,* and *leader satisfaction*—see further details of these strategies in Contreras et al. (2021)). To evaluate the proposed group recommender system, the authors performed a user study in the tourism domain with 68 participants, who were then formed into 17 groups. The experimental results confirm that, by monitoring user interactions, the collaborative model can be developed to infer useful notions of collaboration and leadership. This way, this model helps to generate more effectiveness of group recommendations.

Remark Although consensus approaches taking into account social relationship interactions help to increase the performance of group recommendations, they show two limitations. First, the proposed group recommender systems were tested with small group datasets, which could lead to insufficient and imprecise evaluation results w.r.t the group recommendation performance. Besides, these systems were only examined in two item domains (e.g., movie and tourism), which may not provide sufficient insights into the impacts of social interactions on the proposed consensus model from the item domain perspective (Contreras et al. 2021).

5.3 Consensus approaches based on explanations and visualization methods

When to apply? Consensus approaches based on explanations and visualization methods can be applied when group recommender systems need to provide *consensus explanations* that intuitively describe the current status of group members' preferences and help to resolve potential conflicts among them.

Basic concepts Explanations are often integrated into recommender systems to provide further information regarding the underlying recommendation mechanisms. The integration of explanations can bring different goals, such as *transparency* (explaining how the system works), *scrutability* (telling the system it is wrong), *trust* (inspiring the trust and loyalty of users), *satisfaction* (increasing the system utility and users' joy w.r.t recommended items), *effectiveness* (assisting users on making good decisions), *efficiency* (accelerating users' decision-making processes), and *persuasiveness* (convincing users to consume the recommended items) (Tintarev 2007). Besides the mentioned goals, in the context of group recommendation scenarios, explanations can also provide further goals to better consider social factors in group recommendation scenarios.[12] *Consensus* is a typical example of social factors, indicating the ability of an explanation to help group members resolve conflicts among group members' preferences and accelerate the consensus-achieving process (Felfernig et al. 2018b; Tran et al. 2019). When conflicts among group members' preferences occur, consensus explanations are needed to help group members be aware of the group's current status and proceed with preference adaptations to resolve conflicts. Based on this idea, consensus explanations can be categorized into two types: (1) *explanations showing group members' conflicts* and (2) *explanations resolving group members' conflicts*. In the following, we will provide further discussions regarding these explanation types.

Explanations showing group members' conflicts When there are conflicts among group members, a consensus-achieving process is activated. This process is repeated until the consensus degree of the group is high enough (i.e., not lower than a pre-defined threshold). In each iteration, explanations should be provided to help users be aware of the current consensus state of the group. Information regarding the compatibility of group members' preferences and the current group consensus level can be included in consensus explanations. Some examples of the textual consensus explanations are presented in the following:

- Explanation when the consensus level is *low* (i.e., smaller than a pre-defined threshold): *"The current consensus level of the group is still low because the preferences of user A and user B are highly different"*.
- Explanation when the consensus level is *high* enough: *"The current consensus level of the group reaches the threshold and the consensus process completes"*.

The consensus-achieving process can be hindered by conflicts arising among group members. In order to help detect conflicts, an explanation could be formulated for the group member as follows: *"We have detected that your preference on item X is very different from the preference of user A and user B"*. Preference conflicts can also be graphically represented using different display modes. For instance, Palomares et al. (2014b) use a *set-based graph* to visualize the current group consensus state in different rounds of the consensus-achieving process. In each round, the preferences of all group members are represented in a 2-dimensional space. Each circle in the graph represents a group member. Group members with similar preferences are placed close to each other and gathered into a cluster. This approach enables users to detect disagreement positions within the group. For instance, Fig. 3a shows that two subgroups of users strongly disagree with each other and with the rest of the group members. A consensus-achieving process, therefore, needs to be repeated. At the end of each round, the consensus state is updated for the decision-maker. Figure 3b describes the projections of group members' preferences in the final round of the consensus-achieving process. In this round, most users moved their preferences closer to the agreement position, meaning that they contributed positively to the group consensus achievement. However, there exist some users who did not change their preferences. All detected information about the group consensus situation assists the decision-maker in carrying out appropriate activities for group members. These activ-

[12] Since explanations in group recommender systems are not the focus of this article, we refer to Felfernig et al. (2018b) for further details regarding this topic.

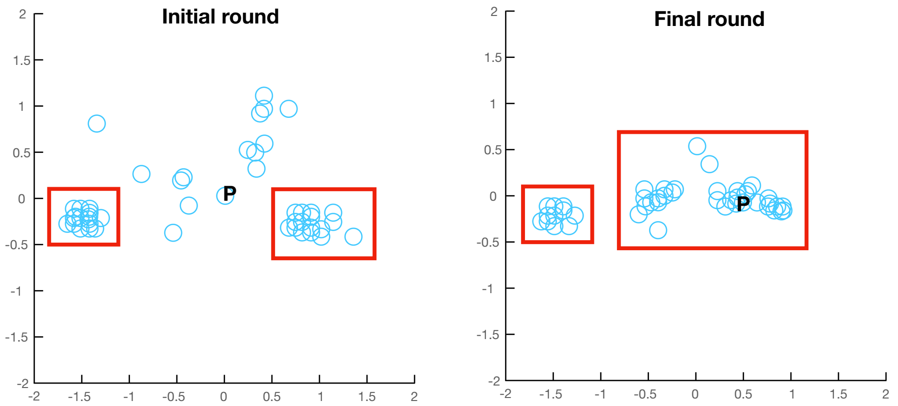
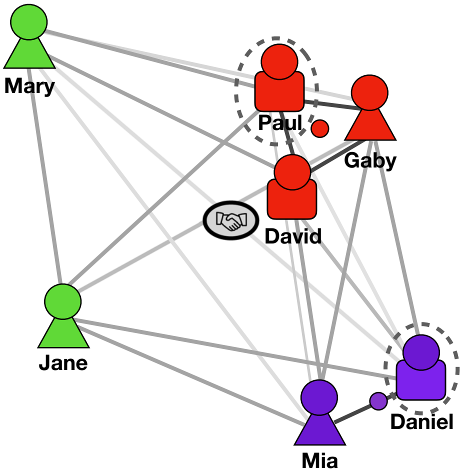


Fig. 3 A set-based graph representing the consensus state of a group in the initial round and in the final round of the consensus-achieving process. In the initial round, two subgroups of users represent a strong disagreement with each other and with the remaining group members. In the final round, many users moved closer to the *collective preference P* (i.e., the preference obtained in the aggregation phase), whereas there were still some users who still needed to adapt their preferences. This figure is based on the original one from the work of Palomares et al. (2014b). Numbers in the axes describe the preference intensity of group members, for instance, −2: completely dislike, and 2: completely like

Fig. 4 A node–link diagram representing preference conflicts among group members. Nodes represent group members, and links represent conflicts between two group members. The length of a link indicates the conflict level between group members. The longer the link, the higher the conflict level between group members. We drew this figure based on the original work of Alonso et al. (2007). The handshake icon in the figure is from https://www.flaticon.com/ (free download version)



ities can be, for instance, informing users (who did not positively contribute to the consensus-achieving process) about moving towards the selection process to make the final decision or penalizing those who did not cooperate with the rest of the group.

In another study, Alonso et al. (2007) visualize the preference conflicts in a group using a *node–link diagram*. The nodes represent group members, and the links show conflicts between them. The longer the link, the higher the conflict level between group members. For instance, the link between Sergio and Antonio indicates a high conflict between these two users (see Fig. 4).

Differing from the two mentioned visualization approaches, Mahyar et al. (2017) represent conflicts among group members using different display methods such as

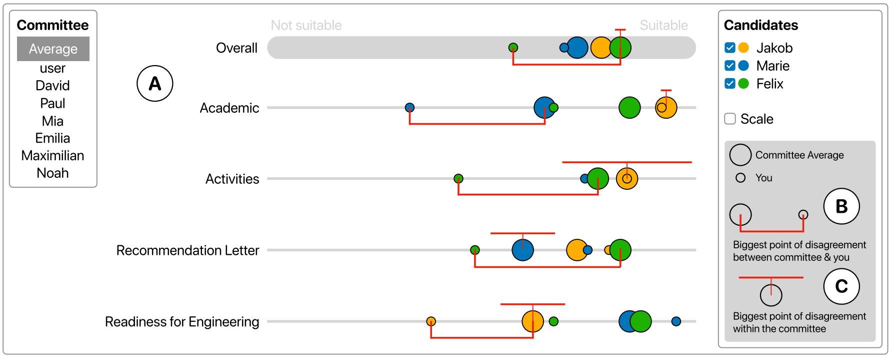


Fig. 5 A visualization approach combining circles, text, lines, and symbols to describe disagreements in a group decision. A small circle represents the preference of a group member, whereas a big one represents the average of group preferences. Each red line shows one of the following disagreements: disagreement between the group and the current user (see *area B*) and disagreement within the group (see *area C*). This figure is drawn based on the original work of Mahyar et al. (2017)

circles, text, lines, and *symbols*. A small circle represents the preference of a group member, whereas a big one represents the average of group preferences. Each red line describes one of the following disagreements: (1) disagreements between individual group members and the rest of the group and (2) disagreements within the group itself (see Fig. 5).

Explanations resolving group members' conflicts Besides helping group members be aware of the conflicts between them, explanations regarding the repair actions are also needed to help them resolve conflicts. One approach to formulating such explanations is to indicate possible changes in group members' preferences. These explanations help group members agree on a solution and improve their satisfaction with the recommended items (Tran et al. 2019). Quijano-Sánchez et al. (2017) propose another approach to generate explanations that convince group members to take items recommended by their close friends or people they trust. A related example explanation is: *"Although your preference for item X is not very high, your close friend A (who you highly trust) thinks it is an excellent choice"*. Najafian and Tintarev (2018) propose explanations that persuade group members to agree on a solution, for instance, *"Item X is recommended because nobody hates it in the group due to the lowest rating determined for user A and supports the highest rating determined for user B"*. The authors also propose repair explanations considering the fairness aspect: *"The system detected that you are not interested in item X, but it is the item that user A likes the most. You made your choice in the previous round. It is now user A's turn"*. Tran et al. (2019) develop explanations convincing group members to agree on a recommended item by considering *decision history* and *future decision plan* in the context of repeated decisions. *Decision history* shows how the preferences of group members were considered in the past decisions. *Future decision plan* shows how the preferences of group members will be taken into account in future decisions. One example of decision history-based explanations is formulated in the following: *"The preference of user A was not taken into account in the last three decisions. Therefore, in* *the ongoing decision, item X has been selected since he/she likes it the most"*. Another example of future decision plan-based explanations is: *"Item X has been recommended to the group since user A likes it the most. However, all group members agreed that the preferences of the other group members should be taken into account in turn in the upcoming decisions"*.

Remark The explanations and visualization approaches presented in this section can be considered *UI-based consensus models* instead of algorithmic consensus models as presented in Sects. 5.1 and 5.2. These approaches support group members' consensus and negotiation processes by showing conflicts among them (Alonso et al. 2007; Mahyar et al. 2017; Palomares et al. 2014b). To accelerate the consensus-achieving process, these approaches also show conflict-related information at the group level, i.e., this information can be seen by all group members. Besides, explanations can also be created as repair solutions that help group members to resolve their conflicts (Quijano-Sánchez et al. 2017; Najafian and Tintarev 2018; Tran et al. 2019). In these approaches, typical social factors such as consensus and fairness have already been taken into account as the basic arguments for the generated explanations. The mentioned approaches show several drawbacks. The effectiveness of consensus explanations has not been sufficiently evaluated. For instance, in the approaches proposed by Alonso et al. (2007), Mahyar et al. (2017), Palomares et al. (2014b), it is still unclear if the proposed explanation/visualization methods help to increase group satisfaction, if the explanation/visualization is updated in real-time or if the consensus-achieving process has already been accelerated thanks to the consensus explanation/visualization. Although explanation approaches for resolving conflicts show some performance improvements in the experimental results, the evaluations were done with small group datasets. Besides, they are synthetic datasets instead of real ones.

6 Open topics for future work

Although the literature has shown various approaches to performing the consensus-achieving process in group decision-making and group recommender systems, some open topics still need to be considered for future work. In this section, we further discuss open issues pointed out by Cabrerizo et al. (2013) and propose corresponding solutions to address them. The issues and related solutions are applied to both contexts, group decision-making and group recommender systems.

6.1 Feedback generation

The feedback mechanism in the consensus-achieving process needs to be activated when the consensus degree of the whole group is lower than a pre-defined consensus threshold. Users whose preferences differ from others' preferences receive suggestions regarding preference adaptation. Although several studies address this, the proposed approaches are solely appropriate for scenarios where preference structures specified by group members are homogeneous (i.e., the same preference formats). In the circumstances of heterogeneous preference structures (i.e., group members use different preference formats to express their preferences), the feedback generation process is still challenging. Therefore, it would be necessary to develop *adaptive consensus models* which can manage different formats of preference structures at the same time.

In addition, the consensus-achieving process is often time-consuming since it needs to be performed in many iterations. Hence, it is essential to propose adaptation mechanisms that guarantee the fast convergence of group members' preferences. In this section, we discuss an idea for a more efficient adaptation mechanism. What came up to our mind is a *group distance-based consensus model*, showing that if a group member adapts his/her preferences close to the *average group preference*, then it helps to quickly bring him/her closer to other group members. Inspired by the work of Gallardo et al. (2015) and Delic et al. (2019) where *centrality scores* are utilized to measure the distance between a group member's preferences to the preferences of the rest of the group, our idea is to compute the consensus degree based on the distance between group members. The lower the distance among group members, the higher the consensus within the whole group. For each item, the distance of each pair of group members is first computed. The distances of all pairs of group members for an item are then aggregated to obtain the *group distance*. Thereafter, the *global group distance* of the whole group for all items is calculated by taking the *average* of group distances of all items. For each round of the consensus-achieving progress, the global group distance is calculated and compared to a pre-defined threshold θ. If the global group distance is not greater than θ, the distance of all group members is acceptable, and the consensus-achieving process completes. Otherwise, a feedback mechanism is activated to let group members adapt their preferences. Group members whose preferences are different from other group members' preferences need to be identified. The user identification can be performed as follows. For each item, the distance between each group member and the others is computed. Group members with the maximum total distance to others will receive feedback regarding preference adaptation. To speed up the consensus-achieving process, the identified group members are encouraged to adapt their preferences for a specific item closer to the *average group preference*. Although we believe this approach could bring a more efficient consensus-achieving process to group members, for future work, we will conduct experimental studies in different domains to prove the efficiency of the proposed consensus model.

6.2 The importance of group members

In several real-life group decision-making problems, there exist situations where some group members have higher importance than others. For instance, in requirements engineering scenarios (Samer et al. 2020) where a group of stakeholders has to select which requirements should be implemented in the next release, project managers or experienced stakeholders might influence the final decision more than other stakeholders. To model such situations, one usual approach is to assign a higher weight to those with a higher importance level (e.g., project managers and experienced stakeholders).

Contreras et al. (2015, 2021) take into account the role of the leader in a group, who provided more feedback to the items proposed to the other group members and therefore has a higher impact on the final decision. Some other consensus models have considered the heterogeneity of the group members when aggregating their preferences into the collective preference (Bouzarour-Amokrane et al. 2015; Herrera et al. 1997). However, this aspect needs to be considered when advising the preference adaptation solutions. Therefore, it is crucial to develop new feedback mechanisms that adjust the amount of advice delivered to group members by considering their knowledge level. It is reasonable that users with lower importance or knowledge level will need more adaptation suggestions compared to more experienced users.

Along with the importance of group members, fairness within the group is also an essential factor that needs to be considered in the consensus-achieving process (Felfernig et al. 2018b). Consensus demands a high level of trust and satisfaction among group members. By the end of the consensus-achieving process, users want to believe that each group member has been treated fairly. Besides, during this process, every group member should honestly do their best to foster fairness. In fact, Hearld et al. (2013) point out that the perceptions of group members regarding fairness in the group decision-making process strongly correlate with the perceived level of consensus among group members. Similar findings have also been found in the work of Tran et al. (2019). These authors show that fairness-related arguments can be exploited to increase the perception of group members in terms of fairness and, therefore, convince them to reach a consensus and agree on a recommended item. However, the results in the mentioned studies need to be further examined since they were just evaluated in synthetic group datasets that do not reflect real group recommendation scenarios. Therefore, further work on fairness in the consensus-achieving process should be performed as part of future work.

6.3 Persuasive arguments

During the consensus-achieving process, one of the most essential tasks of the moderator is to suggest group members whose preferences are far from group preferences to adapt their preferences to increase the consensus degree. However, not every group member is willing to adjust their preferences. Therefore, the challenge in this context is that the moderator needs to find a way to convince group members to adapt their opinions. However, convincing people is a challenging task. Hence, the generation of persuasive arguments should be based on the influential principles introduced by psychologists (Cialdini 2007; Fogg 2002). These principles identify strategies that improve the effectiveness of persuasive arguments. Among them, the six influence strategies proposed by Cialdini (2007) (*reciprocity, scarcity, authority, social proof, liking,* and *commitment*) are the most commonly used in persuasive systems studies (Alslaity and Tran 2020; Gkika et al. 2016):

– *Reciprocation* describes a user's tendency to return favors and pay back others who have given him/her something.
– *Consistency* describes the tendency of a user to be consistent with his/her first opinion.
– *Social proof* indicates a user's tendency to be influenced by similar users.
– *Liking* refers to the tendency of a user to be influenced by people he/she likes.

– *Authority* describes a sense of obligation and duty to users who are in positions of authority.
– *Scarcity* refers to a user's tendency to consider more valuable whatever is scarce.

The mentioned strategies can be utilized to generate convincing arguments that help to change group members' attitudes, beliefs, and behavior and avoid coercion. Besides these strategies, personality has already been recognized as a crucial factor in generating persuasive arguments (Josekutty Thomas et al. 2017). The literature has witnessed several studies investigating the influence of users' personality on the influence-strategy selection (Ciocarlan et al. 2019; Felfernig et al. 2018a; Shmueli-Scheuer et al. 2019; Thomas et al. 2017). However, in the context of recommender systems, only a few studies were conducted to discover the role of users' personality in generating persuasive explanations (Gkika et al. 2016; Alslaity and Tran 2020). The mentioned studies are limited to discussing results regarding the impacts of personality on the persuasiveness of explanations, whereas in-depth studies on how explanations can be enriched with this factor and how they affect the consensus-achieving process (especially in group decision-making and group recommender systems) are still missing. To bridge this gap, one open topic is to develop different techniques to enrich explanations with personality-related information. We believe that developing personality-aware arguments helps to increase users' perception concerning the recommended items (in terms of *"how well the recommended item fits their personality"*). Besides, these arguments can motivate them to consume the items or change their decision behavior. These explanations can also help to increase the satisfaction of users with the recommended items.

6.4 Consensus explanations and visualization

Consensus explanations and effective visualization methods are beneficial for group members to be aware of the current consensus state in the group. Graphical representation could be an effective method that helps group members be aware of differences between his/her preferences and other group members' preferences. Although several approaches to consensus explanations and visualization have been proposed in the current literature (see Sect. 5.2), group members still do not have insights into the consensus state of the group, such as *"where do the conflicts come from?"* or *"which users conflict with each other?"*.

To provide more sufficient information regarding the consensus state, further studies on consensus explanations and visualization need to be performed. One solution can be to use a *node–link diagram* to represent the conflict/agreement between two group members. The diagram consists of *nodes* showing the name of group members and *links* representing the *conflict/agreement* level between group members. The thicker the link, the higher the conflict/agreement level between group members' preferences. The current consensus status of a group of friends in the tourism domain can be visualized as in Fig. 6.

For future work, user studies are needed to evaluate the effectiveness of the proposed visualization method. Besides, one factor that needs to be examined for the proposed method is *privacy*. Najafian and Tintarev (2018) point out that group members do

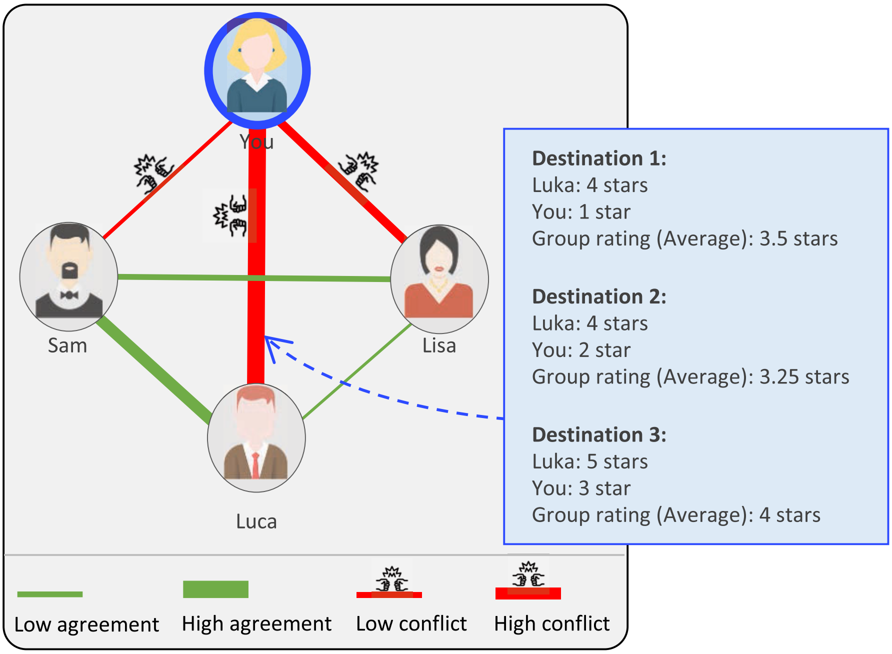


Fig. 6 A proposal of a node–link diagram representing the conflicts/agreements among group members. A node represents a group member and a link represents the conflict/agreement between two individual group members. A link shown as a solid line represents an agreement between two group members. A link shown as a solid line with a conflict icon represents a conflict between two group members. The thickness of a link represents the intensity of a conflict or an agreement. For instance, the current user—you (shown with a thick blue frame) has a *high conflict* with Luca. By clicking on the link, the current user can see the details of the conflict and agreement between her preferences and the preferences of another group member. The conflict icon in the figure is from https://www.flaticon.com/ (free download version). (Color figure online)

not have an equal privacy concern to all types of user information. Given specific information, some users want to disclose it, while some do not. Besides, the needs of users regarding privacy are assumed to be affected by different factors such as *personality, the relationship type in the group*, and *preference scenarios*. Inspired by this work, user studies should be conducted to analyze on which level the preference information should be disclosed (only for each individual group member or for the whole group). Besides, a group member should be able to decide whether he/she wants to disclose his/her preferences to other group members.

6.5 Consensus negotiation

Several studies have been conducted in group recommender systems to overcome the drawbacks of the basic aggregation strategies and generate consensus-based group recommendations. Most of these studies are proposed on the algorithmic level (in the recommendation generation phase) or on the representation level (in the explanation representation phase) that shows consensus explanations to users. However, further open topics can also be discovered in the *consensus negotiation phase* to better support consensus-achieving processes. One promising solution is to enrich user interfaces by integrating negotiation mechanisms among group members. User interfaces are designed in such a way that facilitates group members to share their preferences within the group (Nguyen and Ricci 2017a). Being aware of the preferences of each other helps the group reach a consensus more quickly. An example thereof is the following: user *A* prefers *"cheese"*, whereas user *B* is interested in *"beef"*. A negotiation template can be proposed in this context as follows: *"user* A *would accept recipes with beef as long as they contain cheese"*. The generation of negotiation patterns for the consensus-achieving process is still an open research topic up to now.

7 Conclusion

The consensus-achieving process plays a vital role in group decision-making activities, which helps to achieve a final solution with a high agreement and satisfaction level. This article provides readers with a full landscape of existing consensus models in two contexts—group decision-making and group recommender systems. Consensus models for group decision-making focus on calculating soft consensus measures based on various models such as *reference domain, coincidence method, OWA operators, guidance measures, recommendation generation,* and *individual centrality*. Besides, other approaches supporting the consensus-achieving process in heterogeneous and large-scale groups have also been discussed in this article, such as *clustering methods, consensus-achieving processes, group decision-making methods*, and *group decision-making support systems*. On the other hand, we also discuss different consensus approaches for group recommender systems with different targets, such as *overcoming the limitations of the basic aggregation mechanisms, further taking into account social relationships among group members*, and *achieving highly satisfying group recommendations*. Different consensus approaches based on explanations and visualization are also presented to intuitively describe the current consensus state of the group and accelerate the consensus-achieving process. Although plenty of studies on consensus models have been proposed in the literature, there still exists room to proceed with further improvements in these models in both contexts, group decision-making and group recommender systems.

Funding Open access funding provided by Graz University of Technology.

References

Alonso, S., Herrera-Viedma, E., Cabrerizo, F.J., et al.: Visualizing consensus in group decision making situations. In: IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), pp. 1–6. IEEE, London, UK (2007)

Alonso, S., Chiclana, F., Herrera, F., et al.: A consistency-based procedure to estimate missing pairwise preference relations. Int. J. Intell. Syst. **23**, 155–175 (2008)

Alonso, S., Pérez, I., Cabrerizo, F., et al.: A linguistic consensus model for web 2.0 communities. Appl. Soft Comput. **13**(1), 149–157 (2013)

Alslaity, A., Tran, T.: The effect of personality traits on persuading recommender system users. In: Brusilovsky, P., de Gemmis, M., Felfernig, A., et al. (eds) Proceedings of the 7th Joint Workshop on Interfaces and Human Decision Making for Recommender Systems co-located with 14th ACM Conference on Recommender Systems (RecSys 2020), Online Event, September 26, 2020, CEUR Workshop Proceedings, vol. 2682. pp. 48–56. CEUR-WS.org, Aachen, Germany (2020)

Ardissono, L., Goy, A., Petrone, G., et al.: Intrigue: Personalized recommendation of tourist attractions for desktop and hand held devices. Appl. Artif. Intell. **17**(8–9), 687–714 (2003)

Atas, M., Tran, T., Samer, R., et al.: Liquid democracy in group-based configuration. In: Proceedings of the 20th Configuration Workshop, Graz, Austria, September 27–28, 2018., pp. 93–98, 20th International Workshop on Configuration, ConfWS; Conference date: 27-09-2018 Through 28-09-2018 (2018)

Bahari Sojahrood, Z., Taleai, M., Cheng, H.: Hybrid poi group recommender system based on group type in LBSN. Expert Syst. Appl. **219**(C), 1–9 (2023)

Ben-Arieh, D., Chen, Z.: Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations. IEEE Trans. Syst. Man Cybern. Part A: Syst. Hum. **36**(3), 558–568 (2006)

Bordogna, G., Fedrizzi, M., Pasi, G.: A linguistic approach to the evaluation of consensus in group decision making. In: Proceedings of the Fifth International Workshop on Current Issues on Fuzzy Technologies (CIFT'95), Trento, pp. 7–13 (1995)

Borowik, G., Kraśniewski, A., Łuba, T.: Rule induction based on logic synthesis methods. In: Selvaraj, H., Zydek, D., Chmaj, G. (eds.) Progress in Systems Engineering, pp. 813–816. Springer, Cham (2015)

Boulkrinat, S., Hadjali, A., Mokhtari, A.: Crowd-voting-based group recommender systems. In: 12th International Symposium on Programming and Systems (ISPS' 2015), pp. 1–9 (2015)

Bouzarour-Amokrane, Y., Tchangani, A., Peres, F.: A bipolar consensus approach for group decision making problems. Expert Syst. Appl. **42**(3), 1759–1772 (2015)

Brafman, R.I., Domshlak, C.: Preference handling: an introductory tutorial. AI Mag. **30**(1), 58–86 (2009)

Bryson, N.: Group decision-making and the analytic hierarchy process: exploring the consensus-relevant information content. Comput. Oper. Res. **23**(1), 27–35 (1996)

Büyüközkan, G.: Multi-criteria decision making for e-marketplace selection. Internet Res. **14**(2), 139–154 (2004)

Cabrerizo, F.J., Alonso, S., Herrera-Viedma, E.: A consensus model for group decision making problems with unbalanced fuzzy linguistic information. Int. J. Inf. Technol. Decis. Mak. **8**, 109–131 (2009)

Cabrerizo, F.J., Alonso, S., Herrera-Viedma, E.: A consensus model for group decision making problems with unbalanced fuzzy linguistic information. Int. J. Inf. Technol. Decis. Mak. **8**(1), 109–131 (2009)

Cabrerizo, F.J., Heradio, R., Pérez, I.J., et al.: A selection process based on additive consistency to deal with incomplete fuzzy linguistic information. J. Univers. Comput. Sci. **16**(1), 62–81 (2010)

Cabrerizo, F.J., Pérez, I.J., Herrera-Viedma, E.: Managing the consensus in group decision making in an unbalanced fuzzy linguistic context with incomplete information. Knowl.-Based Syst. **23**(2), 169–181 (2010)

Cabrerizo, F.J., Chiclana, F., Ureña, R., et al.: Challenges and open questions in soft consensus models. In: Joint IFSA World Congress and NAFIPS Annual Meeting, IFSA/NAFIPS 2013, Edmonton, Alberta, Canada, June 24–28, 2013, pp. 944–949 (2013)

Cabrerizo, F.J., Morente-Molinera, J.A., Pérez, I.J., et al.: A decision support system to develop a quality management in academic digital libraries. Inf. Sci. **323**(C), 48–58 (2015)

Cabrerizo, F.J., Al-Hmouz, R., Morfeq, A., et al.: Soft consensus measures in group decision making using unbalanced fuzzy linguistic information. Soft. Comput. **21**(11), 3037–3050 (2017)

Cabrerizo, F.J., Pérez, I.J., Chiclana, F., et al.: Group Decision Making: Consensus Approaches Based on Soft Consensus Measures, pp. 307–321. Springer, Cham (2017)

Carlsson, C., Ehrenberg, D., Eklund, P., et al.: Consensus in distributed soft environments. Eur. J. Oper. Res. **61**(1), 165–185 (1992)

Carvalho, G., Vivacqua, A.S., Souza, J.M., et al.: LaSca: a large scale group decision support system. In: 2008 12th International Conference on Computer Supported Cooperative Work in Design, pp. 289–294 (2008)

Castro, J., Quesada, F.J., Palomares, I., et al.: A consensus-driven group recommender system. Int. J. Intell. Syst. **30**(8), 887–906 (2015)

Castro, J., Lu, J., Zhang, G., et al.: Opinion dynamics-based group recommender systems. IEEE Trans. Syst. Man. Cybern.: Syst. **48**(12), 2394–2406 (2018)

Cerquides, J., López-Sánchez, M., Reyes-Moro, A., et al.: Enabling assisted strategic negotiations in actual-world procurement scenarios. Electron. Commer. Res. **7**(3–4), 189–220 (2007)

Chen, J.L., Chen, C., Wang, C.C., et al.: Measuring soft consensus in uncertain linguistic group decision-making based on deviation and overlap degrees. Int. J. Innov. Manag. Inf. Prod. **3**(1), 25–33 (2012)

Chen, X.H., Liu, R.: Improved clustering algorithm and its application in complex huge group decision-making. Syst. Eng. Electron. **28**, 1695–1699 (2006)

Chiclana, F., Herrera-Viedma, E., Herrera, F., et al.: Some induced ordered weighted averaging operators and their use for solving group decision-making problems based on fuzzy preference relations. Eur. J. Oper. Res. **182**, 383–399 (2007)

Choudhary, N., Minz, S., Bharadwaj, K.K.: Negotiation framework for group recommendation based on fuzzy computational model of trust and distrust. Multimedia Tools Appl. **79**(37–38), 27337–27364 (2020)

Cialdini, R.B.: Influence: The Psychology of Persuasion. Harper Collins, New York (2007)

Ciocarlan, A., Masthoff, J., Oren, N.: Actual persuasiveness: impact of personality, age and gender on message type susceptibility. In: Oinas-Kukkonen, H., Win, K.T., Karapanos, E., et al. (eds.) Persuasive Technology: Development of Persuasive and Behavior Change Support Systems, pp. 283–294. Springer, Cham (2019)

Contreras, D., Salamó, M., Pascual, J.: A web-based environment to support online and collaborative group recommendation scenarios. Appl. Artif. Intell. **29**(5), 480–499 (2015)

Contreras, D., Salamó, M., Boratto, L.: Integrating collaboration and leadership in conversational group recommender systems. ACM Trans. Inf. Syst. **39**(4), 1–32 (2021)

Crossen, A., Budzik, J., Hammond, K.J.: Flytrap: intelligent group music recommendation. In: Proceedings of the 7th International Conference on Intelligent User Interfaces. Association for Computing Machinery, New York, NY, USA, IUI ’02, pp. 184—185 (2002)

Csiszar, O.: Ordered weighted averaging operators: a short review. IEEE Syst. Man Cybern. Mag. **7**(2), 4–12 (2021)

Degroot, M.H.: Reaching a consensus. J. Am. Stat. Assoc. **69**(345), 118–121 (1974)

Delic, A., Ricci, F., Neidhardt, J.: Preference networks and non-linear preferences in group recommendations. In: IEEE/WIC/ACM International Conference on Web Intelligence. Association for Computing Machinery, New York, NY, USA, WI ’19, pp. 403–407 (2019)

Dong, Y., Zhang, H.: Multiperson decision making with different preference representation structures: a direct consensus framework and its properties. Know-Based Syst. **58**, 45–57 (2014)

Dong, Y., Hong, W., Xu, Y.: Measuring consistency of linguistic preference relations: a 2-tuple linguistic approach. Soft. Comput. **17**, 2117–2130 (2013)

Dong, Y., Chen, X., Liang, H., et al.: Dynamics of linguistic opinion formation in bounded confidence model. Inf. Fusion **32**, 52–61 (2016)

Dong, Y., Zhang, H., Herrera-Viedma, E.: Integrating experts’ weights generated dynamically into the consensus reaching process and its applications in managing non-cooperative behaviors. Decis. Support Syst. **84**, 1–15 (2016)

Emamgholizadeh, H.: Supporting group decision-making processes based on group dynamics. In: Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization. Association for Computing Machinery, New York, NY, USA, UMAP ’22, pp. 346–350 (2022)

Endriss, U.: Monotonic concession protocols for multilateral negotiation. In: Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems. Association for Computing Machinery, New York, NY, USA, AAMAS ’06, pp. 392–399 (2006)

Fedrizzi, M., Kacprzyk, J.: Consensus degrees under fuzzy majorities and fuzzy preferences using OWA (ordered weighed average) operators. Control Cybernet. **22**, 78–86 (1993)

Fedrizzi, M., Mich, L.: Rule based model for consensus reaching group decisions support. In: IPMU 1992 Conference on Information Processing and Management of Uncertainty in Knowledge-Based System. Mallorca, Spain, pp. 301–304 (1992)
Fedrizzi, M., Kacprzyk, J., Zadrozny, S.: An interactive multi-user decision support system for consensus reaching processes using fuzzy logic with linguistic quantifiers. Decis. Support Syst. **4**(3), 313–327 (1988)
Fedrizzi, M., Ferizzi, M., Pereira, R.A.M.: On the issue of consistency in dynamical consensual aggregation. Technol. Construct. Intell. Syst. **1**, 129–137 (2002)
Felfernig, A., Atas, M., Helic, D., et al.: Group Recommender Systems: An Introduction, Springer, NY, USA, chap Algorithms for Group Recommendation, pp. 27–58 (2018a)
Felfernig, A., Tintarev, N., Tran, T.N.T., et al.: Group Recommender Systems: An Introduction, Springer, NY, USA, chap Explanations for Groups, pp. 105–126 (2018b)
Fogg, B.J.: Persuasive Technology: Using Computers to Change What We Think and Do. Morgan Kaufmann, San Francisco (2002)
Gallardo, J.C., Real, F.J.Q., Palomares, I., et al.: A consensus-driven group recommender system. Int. J. Intell. Syst. **30**(8), 887–906 (2015)
Gartrell, M., Xing, X., Lv, Q., et al.: Enhancing group recommendation by incorporating social relationship interactions. In: Proceedings of the 2010 ACM International Conference on Supporting Group Work. Association for Computing Machinery, New York, NY, USA, GROUP '10, pp. 97–106 (2010)
Ghaemmaghami, S.S., Abari, A.S.: Deepgroup: group recommendation with implicit feedback. In: Proceedings of the 30th ACM International Conference on Information and Knowledge Management. Association for Computing Machinery, New York, NY, USA, CIKM '21, pp. 3408–3412 (2021)
Girdhar, N., Minz, S., Bharadwaj, K.K.: Link prediction in signed social networks based on fuzzy computational model of trust and distrust. Soft. Comput. **23**(22), 12123–12138 (2019)
Gkika, S., Skiada, M., Lekakos, G., et al.: Investigating the role of personality traits and influence strategies on the persuasive effect of personalized recommendations. In: Proceedings of the 4th Workshop on Emotions and Personality in Personalized Systems co-located with ACM Conference on Recommender Systems (RecSys 2016). CEUR Workshop Proceedings, Aachen, Germany, pp. 9–17 (2016)
Gou, X., Xu, Z., Herrera, F.: Consensus reaching process for large-scale group decision making with double hierarchy hesitant fuzzy linguistic preference relations. Knowl.-Based Syst. **157**, 20–33 (2018)
Gouran, D.S., Hirokawa, R.: Functional theory and communication in decision-making and problem-solving groups: an expanded view. Communication and Group Decision Making, pp. 55–80 (1996)
Gross, T.: Towards a better understanding of negotiation in group recommender systems. In: Proceedings of Mensch Und Computer 2019. Association for Computing Machinery, New York, MuC'19, pp. 559–563 (2019)
He, W., Dutta, B., Rodríguez, R.M., et al.: Induced OWA operator for group decision making dealing with extended comparative linguistic expressions with symbolic translation. Mathematics **9**(1), 1–20 (2021)
Hearld, L., Alexander, J., Wolf, L., et al.: Decision-making fairness and consensus building in multisector community health alliances: a mixed-methods analysis. Nonprofit Manag. Leadersh. **24**, 139–161 (2013)
Herrera, F., Herrera-Viedma, E., Verdegay, J.L.: A sequential selection process in group decision making with a linguistic assessment approach. Inf. Sci. **85**(4), 223–239 (1995)
Herrera, F., Herrera-Viedma, E., Verdegay, J.L.: A model of consensus in group decision making under linguistic assessments. Fuzzy Sets Syst. **78**(1), 73–87 (1996)
Herrera, F., Herrera-Viedma, E., Verdegay, J.L.: A rational consensus model in group decision making using linguistic assessments. Fuzzy Sets Syst. **88**(1), 31–49 (1997)
Herrera-Viedma, E., Herrera, F., Chiclana, F.: A consensus model for multiperson decision making with different preference structures. IEEE Trans. Syst. Man Cybern. Part A **32**(3), 394–402 (2002)
Herrera-Viedma, E., Martínez-López, L., Mata, F., et al.: A consensus support system model for group decision-making problems with multigranular linguistic preference relations. IEEE Trans. Fuzzy Syst. **13**, 644–658 (2005)
Herrera-Viedma, E., Alonso, S., Chiclana, F., et al.: A consensus model for group decision making with incomplete fuzzy preference relations. IEEE Trans. Fuzzy Syst. **15**(5), 863–877 (2007)
Herrera-Viedma, E., Cabrerizo, F.J., Kacprzyk, J., et al.: A review of soft consensus models in a fuzzy environment. Inf. Fusion **17**, 4–13 (2014)

Huang, S., Wang, S., Liu, T.Y., et al.: Listwise collaborative filtering. In: Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. Association for Computing Machinery, New York, NY, USA, SIGIR '15, pp. 343–352 (2015)

Huang, S.L.: Designing utility-based recommender systems for e-commerce: evaluation of preference-elicitation methods. Electron. Commer. Res. Appl. **10**(4), 398–407 (2011)

Jameson, A.: More than the sum of its members: challenges for group recommender systems. In: Proceedings of the Working Conference on Advanced Visual Interfaces. Association for Computing Machinery, New York, NY, USA, AVI '04, pp. 48–54 (2004)

Jameson, A., Smyth, B.: Recommendation to groups. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The Adaptive Web: Methods and Strategies of Web Personalization, pp. 596–627. Springer, Berlin (2007)

Jannach, D., Manzoor, A., Cai, W., et al.: A survey on conversational recommender systems. ACM Comput. Surv. **54**(5), 1–36 (2021)

Josekutty Thomas, R., Masthoff, J., Oren, N.: Personalising healthy eating messages to age, gender and personality: using cialdini's principles and framing. In: Proceedings of the 22nd International Conference on Intelligent User Interfaces Companion. Association for Computing Machinery, New York, NY, USA, IUI '17 Companion, pp. 81–84 (2017)

Kacprzyk, J.: Group decision making with a fuzzy linguistic majority. Fuzzy Sets Syst. **18**(2), 105–118 (1986)

Kacprzyk, J.: On some fuzzy cores and "soft" consensus measures in group decision making. The Analysis of Fuzzy Information, pp. 119–130 (1987)

Kacprzyk, J., Fedrizzi, M.: A 'soft' measure of consensus in the setting of partial (fuzzy) preferences. Eur. J. Oper. Res. **34**(3), 316–325 (1988)

Kacprzyk, J., Fedrizzi, M.: A 'human-consistent' degree of consensus based on fuzzy logic with linguistic quantifiers. Math. Soc. Sci. **18**(3), 275–290 (1989)

Kacprzyk, J., Fedrizzi, M., Nurmi, H.: Group decision making and consensus under fuzzy preferences and fuzzy majority. Fuzzy Sets Syst. **49**(1), 21–31 (1992)

Kacprzyk, J., Zadrozny, S., Ras, Z.W.: Action rules in consensus reaching process support. In: ISDA' 2009, pp. 827–832. IEEE Computer Society, Redmond, WA (2009)

Kacprzyk, J., Zadrozny, S., Ras, Z.W.: How to support consensus reaching using action rules: a novel approach. Int. J. Uncertain Fuzziness Knowl. Based Syst. **18**(4), 451–470 (2010)

Kalloori, S., Ricci, F., Gennari, R.: Eliciting pairwise preferences in recommender systems. In: Proceedings of the 12th ACM Conference on Recommender Systems. Association for Computing Machinery, New York, NY, USA, RecSys '18, pp. 329–337 (2018)

Kant, V.: Fuzzy computational models of trust and distrust for enhanced recommendations. Int. J. Intell. Syst. **28**, 1–12 (2013)

Kapcak, O., Spagnoli, S., Robbemond, V., et al.: Tourexplain: a crowdsourcing pipeline for generating explanations for groups of tourists. In: Proceedings of the Workshop on Recommenders in Tourism, RecTour 2018, co-located with the 12th ACM Conference on Recommender Systems (RecSys 2018), Vancouver, Canada, October 7, 2018., pp. 33–36 (2018)

Kapoor, S.: A review of attacks and its detection attributes on collaborative recommender systems. Int. J. Adv. Res. Comput. Sci. **8**(7), 1188–1193 (2017)

Kim, J.: A model and case for supporting participatory public decision making in e-democracy. Group Decis. Negot. **17**(3), 179–193 (2008)

Kuncheva, L.I., Krishnapuram, R.: A fuzzy consensus aggregation operator. Fuzzy Sets Syst. **79**(3), 347–356 (1996)

Labella, Á., Liu, Y., Rodríguez, R., et al.: Analyzing the performance of classical consensus models in large scale group decision making: a comparative study. Appl. Soft Comput. **67**, 677–690 (2018)

Li, W., Mo, J., Xin, M., et al.: An optimized trust model integrated with linear features for cyber-enabled recommendation services. J. Parallel Distrib. Comput. **118**, 81–88 (2018)

Lieberman, H., Van Dyke, N.W., Vivacqua, A.S.: Let's browse: a collaborative web browsing agent. In: Proceedings of the 4th International Conference on Intelligent User Interfaces, pp. 65–68. Association for Computing Machinery, New York, NY, USA, IUI '99 (1998)

Liu, B., Shen, Y., Chen, X., et al.: A partial binary tree DEA-DA cyclic classification model for decision makers in complex multi-attribute large-group interval-valued intuitionistic fuzzy decision-making problems. Inf. Fusion **18**, 119–130 (2014)

Liu, Y., Liang, C., Chiclana, F., et al.: A trust induced recommendation mechanism for reaching consensus in group decision making. Knowl.-Based Syst. **119**, 221–231 (2016)

Mahyar, N., Liu, W., Xiao, S., et al.: Consensus: visualizing points of disagreement for multi-criteria collaborative decision making. In: Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing, CSCW 2017, Portland, OR, USA, February 25–March 1, 2017, Companion Volume, pp. 17–20 (2017)
Masthoff, J.: Group Recommender Systems: Combining Individual Models, pp. 677–702. Springer, USA (2011)
Masthoff, J.: Group Recommender Systems: Aggregation, Satisfaction and Group Attributes, pp. 743–776. Springer, Boston (2015)
Masthoff, J., Delić, A.: Group Recommender Systems: Beyond Preference Aggregation, pp. 381–420. Springer, New York (2022)
Masthoff, J., Gatt, A.: In pursuit of satisfaction and the prevention of embarrassment: affective state in group recommender systems. User Model. User-Adap. Inter. **16**(3–4), 281–319 (2006)
Mata, F., Martínez, L., Herrera-Viedma, E.: An adaptive consensus support model for group decision making problems in a multi-granular fuzzy linguistic context. IEEE Trans. Fuzzy Syst. 279–290 (2009)
Merigo, J.M., Gil-Lafuente, A.: OWA operators in generalized distances. Int. J. Math. Comput. Sci. **5**, 11–18 (2009)
Merigó, J.M., Casanovas, M.: Decision-making with distance measures and induced aggregation operators. Comput. Ind. Eng. **60**(1), 66–76 (2011)
Mich, L., Gaio, L., Fedrizzi, M.: On fuzzy logic-based consensus in group decision. In: 5th IFSA World Congress at: Seoul, Korea, pp. 698–700 (1993)
Najafian, S.: Generating natural language explanations for group recommendations in high divergence scenarios. In: Proceedings of the 25th International Conference on Intelligent User Interfaces Companion. Association for Computing Machinery, New York, NY, USA, IUI '20, pp. 31–32 (2020)
Najafian, S., Tintarev, N.: Generating consensus explanations for group recommendations: an exploratory study. In: Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization. Association for Computing Machinery, New York, NY, USA, UMAP '18, pp. 245–250 (2018)
Nguyen, T.N.: Conversational group recommender systems. In: Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization. Association for Computing Machinery, New York, NY, USA, UMAP '17, pp. 331–334 (2017)
Nguyen, T.N., Ricci, F.: A Chat-Based Group Recommender System for Tourism, pp. 17–30. Springer, Cham (2017)
Nguyen, T.N., Ricci, F.: Dynamic elicitation of user preferences in a chat-based group recommender system. In: Proceedings of the Symposium on Applied Computing. Association for Computing Machinery, New York, NY, USA, SAC '17, pp. 1685–1692 (2017b)
Nguyen, T.N., Ricci, F.: Situation-dependent combination of long-term and session-based preferences in group recommendations: an experimental analysis. In: Proceedings of the 33rd Annual ACM Symposium on Applied Computing. Association for Computing Machinery, New York, NY, USA, SAC '18, pp. 1366–1373 (2018)
Ninaus, G., Felfernig, A., Stettinger, M., et al.: Intellireq: Intelligent techniques for software requirements engineering. In: Prestigious Applications of Intelligent Systems (PAIS), pp. 1161–1166 (2014)
O'Connor, M., Cosley, D., Konstan, J.A., et al.: Polylens: A recommender system for groups of users. In: ECSCW'01: Proceedings of the seventh conference on European Conference on Computer Supported Cooperative Work. Kluwer, USA, pp. 199–218 (2001)
Omar, J., Márquez, A., Ziegler, J.: Hootle+: A group recommender system supporting preference negotiation. In: Proceedings of the Collaboration and Technology. Springer, Maastricht, the Netherlands, CRIWG'16, pp. 151–166 (2016)
Orlovsky, S.A.: Decision-making with a fuzzy preference relation. Fuzzy Sets Syst. **1**(3), 155–167 (1978)
Ortega, F., Hernando, A., Bobadilla, J., et al.: Recommending items to group of users using matrix factorization based collaborative filtering. Inf. Sci. **345**, 313–324 (2016)
Palomares, I., Martinez, L.: A semisupervised multiagent system model to support consensus-reaching processes. IEEE Trans. Fuzzy Syst. **22**, 762–777 (2014)
Palomares, I., Martínez-López, L., Herrera, F.: A consensus model to detect and manage non-cooperative behaviors in large-scale group decision making. IEEE Trans Fuzzy Syst. **22**(3), 516–530 (2014)
Palomares, I., Martínez, L., Herrera, F.: Mentor: a graphical monitoring tool of preferences evolution in large-scale group decision making. Knowl.-Based Syst. **58**, 66–74 (2014)

Palomeres, I., Liu, J., Martínez, L.: Modeling attitudes towards consensus in group decision making by means of OWA operators. Int. J. Inf. Technol. Decis. Mak., 1–22 (2011)

Pan, X., Wang, Y., He, S., et al.: A dynamic programming algorithm based clustering model and its application to interval type-2 fuzzy large-scale group decision-making problem. IEEE Trans. Fuzzy Syst. **30**(1), 108–120 (2022)

Pawlak, Z.: Information systems theoretical foundations. Inf. Syst. **6**(3), 205–218 (1981)

Pincay, J., Terán, L., Portmann, E.: Health recommender systems: a state-of-the-art review. In: Sixth International Conference on eDemocracy eGovernment (ICEDEG). IEEE, Quito, Ecuador, pp. 47–55 (2019)

Porro, O., Agell, N., Sánchez, M., et al.: A multi-attribute group decision model based on unbalanced and multi-granular linguistic information: an application to assess entrepreneurial competencies in secondary schools. Appl. Soft Comput. **111**, 107–662 (2021)

Pérez-Almaguer, Y., Yera, R., Alzahrani, A.A., et al.: Content-based group recommender systems: a general taxonomy and further improvements. Expert Syst. Appl. **184**, 115–444 (2021)

Quesada, F.J., Palomares, I., Martínez, L.: Managing experts behavior in large-scale consensus reaching processes with uninorm aggregation operators. Appl. Soft Comput. **35**, 873–887 (2015)

Quijano-Sánchez, L., Sauer, C., Recio-García, J.A., et al.: Make it personal: a social explanation system applied to group recommendations. Expert Syst. Appl. **76**, 36–48 (2017)

Ras, Z.W., Wieczorkowska, A.: Action-Rules: How to increase profit of a company. In: PKDD, Lecture Notes in Computer Science, vol. 1910, pp. 587–592. Springer, NY, USA (2000)

Rodríguez, R.M., Martinez, L., Herrera, F.: Hesitant fuzzy linguistic term sets for decision making. IEEE Trans. Fuzzy Syst. **20**(1), 109–119 (2012)

Rodríguez, R.M., Labella, Álvaro., Tré, G.D., et al.: A large scale consensus reaching process managing group hesitation. Knowl.-Based Syst. **159**, 86–97 (2018)

Rothstein, A., Butler, C.T.: On Conflict and Consensus: A Handbook on Formal Consensus Decision Making. Food Not Bombs, New Mexico, USA (1987)

Rusinowska, A., Eklund, P., Swart, H.D.: Consensus reaching in committees. Eur. J. Oper. Res. **178**(1), 185–193 (2007)

Saaty, T.L.: Multicriteria Decision Making: The Analysis Hierarchy Process. RWS Publications, Pittsburgh (1990)

Salamó, M., McCarthy, K., Smyth, B.: Generating recommendations for consensus negotiation in group personalization services. Pers Ubiquitous Comput. **16**(5), 597–610 (2012)

Samer, R., Stettinger, M., Felfernig, A.: Group recommender user interfaces for improving requirements prioritization. In: Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization. Association for Computing Machinery, New York, NY, USA, UMAP '20, pp. 221–229 (2020)

Sarin, R.K.: Multi-attribute Utility Theory, pp. 1004–1006. Springer, USA (2013)

Schiaffino, S., Godoy, D., Pace, J.A.D., et al.: A mas-based approach for poi group recommendation in LBSN. In: Demazeau, Y., Holvoet, T., Corchado, J.M., et al. (eds.) Advances in Practical Applications of Agents, Multi-Agent Systems, and Trustworthiness, pp. 238–250. Springer, Cham, The PAAMS Collection (2020)

Sebastiá, L., Giret, A., Garcia, I.: A multi agent architecture for tourism recommendation. In: Practical Applications of Agents and Multi-Agent Systems, pp. 547–554 (2010)

Sebastia, L., Giret, A., García, I.: A multi agent architecture for single user and group recommendation in the tourism domain. Int. J. Artif. Intell. **6**, 161–182 (2011)

Shmueli-Scheuer, M., Herzig, J., Konopnicki, D., et al.: Detecting Persuasive Arguments Based on Author-Reader Personality Traits and Their Interaction, pp. 211–215. Association for Computing Machinery, New York (2019)

Srdjevic, B.: Linking analytic hierarchy process and social choice methods to support group decision-making in water management. Decis. Support Syst. **42**(4), 2261–2273 (2007). (**Decision Support Systems in Emerging Economies**)

Stark, B., Knahl, C., Aydin, M., et al.: A literature review on medicine recommender systems. Int. J. Adv. Comput. Sci. Appl. **10**(8), 6–13 (2019)

Tang, M., Liao, H.: Multi-attribute large-scale group decision making with data mining and subgroup leaders: an application to the development of the circular economy. Technol. Forecast. Soc. Change. **167**(120), 719 (2021)

Tang, M., Liao, H., Herrera-Viedma, E., et al.: A dynamic adaptive subgroup-to-subgroup compatibility-based conflict detection and resolution model for multicriteria large-scale group decision making. IEEE Trans. Cybern. **51**(10), 4784–4795 (2021)

Tanino, T.: Fuzzy preference orderings in group decision making. Fuzzy Sets Syst. **12**(2), 117–131 (1984)

Tchangani, A.P.: Evaluation model for multiattributes-multiagents decision making: satisficing game approach. Int. J. Inf. Technol. Decis. Mak. **8**(1), 73–91 (2009)

Tchangani, A.P., Bouzarour-Amokrane, Y., Pérès, F.: Evaluation model in decision analysis: bipolar approach. Informatica **23**(3), 461–485 (2012)

Thomas, R.J., Masthoff, J., Oren, N.: Adapting healthy eating messages to personality. In: Proceedings of the 12th International Conference on Persuasive Technology, PERSUASIVE 2017, pp. 119–132. Springer, Berlin (2017)

Tintarev, N.: Explanations of recommendations. In: Proceedings of the 2007 ACM Conference on Recommender Systems. Association for Computing Machinery, New York, NY, USA, RecSys '07, pp. 203–206 (2007)

Tran, T.N.T., Atas, M., Felfernig, A., et al.: Investigating serial position effects in sequential group decision making. In: Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization, pp. 239–243. Association for Computing Machinery, New York, NY, USA, UMAP '18 (2018)

Tran, T.N.T., Atas, M., Felfernig, A., et al.: Towards social choice-based explanations in group recommender systems. In: Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization. ACM, New York, NY, USA, UMAP '19, pp. 13–21 (2019)

Tundjungsari, V., Istiyanto, J.E., Winarko, E., et al.: Achieving consensus with individual centrality approach. 105–117 (2012). CoRR arXiv:1203.5570

Turoff, M., Hiltz, S., Cho, H.K., et al.: Social decision support systems (SDSS). In: Proceedings of the Annual Hawaii International Conference on System Sciences 81–90 (2002)

Urena, R., Kou, G., Dong, Y., et al.: A review on trust propagation and opinion dynamics in social networks and group decision making frameworks. Inf. Sci. **478**, 461–475 (2019)

Villavicencio, C., Schiaffino, S., Andres Diaz-Pace, J., et al.: Group recommender systems: a multi-agent solution. Knowl.-Based Syst. **164**, 436–458 (2019)

Wang, Y., Li, L., Liu, G.: Social context-aware trust inference for trust enhancement in social network based recommendations on service providers. World Wide Web **18**, 159–184 (2013)

Wu, Z., Xu, J.: A consistency and consensus based decision support model for group decision making with multiplicative preference relations. Decis. Support Syst. **52**(3), 757–767 (2012)

Wu, Z., Xu, J.: A consensus model for large-scale group decision making with hesitant fuzzy information and changeable clusters. Inf. Fusion **41**, 217–231 (2018)

Xiao, J., Wang, X., Zhang, H.: Managing personalized individual semantics and consensus in linguistic distribution large-scale group decision making. Inf. Fusion **53**, 20–34 (2020)

Xu, X.H., Zj, Du., Chen, X.H.: Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions. Decis. Support Syst. **79**, 150–160 (2015)

Yager, R.: On ordered weighted averaging aggregation operators in multicriteria decision making. IEEE Trans. Syst. Man Cybern. **18**(1), 183–190 (1988)

Yager, R.: OWA aggregation over a continuous interval argument with applications to decision making. IEEE Trans. Syst. Man Cybern. Part B (Cybernetics) **34**(5), 1952–1963 (2004)

Yager, R.R.: Penalizing strategic preference manipulation in multi-agent decision making. Trans. Fuzzy Syst. **9**(3), 393–403 (2001)

Yera, R., Álvaro Labella, Castro, J., et al.: On group recommendation supported by a minimum cost consensus model. In: Conference on Data Science and Knowledge Engineering for Sensing Decision Support (FLINS' 2018), pp. 227–234 (2018)

Zadeh, L.A.: A computational approach to fuzzy quantifiers in natural languages. In: Cercone, N. (ed.) Computational Linguistics, pp. 149–184. International Series in Modern Applied Mathematics and Computer Science, Pergamon, Oxford (1983)

Zahir, S.: Clusters in a group: Decision making in the vector space formulation of the analytic hierarchy process. Eur. J. Oper. Res. **112**(3), 620–634 (1999)

Zahir, S.: Geometry of decision making and the vector space formulation of the analytic hierarchy process. Eur. J. Oper. Res. **112**(2), 373–396 (1999)

Zhang, G., Dong, Y., Xu, Y., et al.: Minimum-cost consensus models under aggregation operators. IEEE Trans. Syst. Man Cybern. - Part A: Syst. Hum. **41**(6), 1253–1261 (2011)

Zhang, G., Dong, Y., Xu, Y.: Consistency and consensus measures for linguistic preference relations based on distribution assessments. Inf. Fusion **17**, 46–55 (2014)

Zhang, H., Xiao, J., Palomares, I., et al.: Linguistic distribution-based optimization approach for large-scale GDM with comparative linguistic information: an application on the selection of wastewater disinfection technology. IEEE Trans. Fuzzy Syst. **28**(2), 376–389 (2020)

Zhao, M., Lui, T., Su, J., et al.: A method adjusting consistency and consensus for group decision-making problems with hesitant fuzzy linguistic preference relations based on discrete fuzzy numbers. Complexity **2018**, 1–17 (2018)

Thi Ngoc Trang Tran is a computer scientist who currently works as a Postdoctoral Researcher at the Institute of Software Technology, Graz University of Technology. Prior to her current position, Dr. Tran served more than 10 years as a lecturer at Hue University (Vietnam), where she shared her knowledge and expertise with enthusiastic students. She received her undergraduate and MSc. degrees in Computer Science from Hue University of Sciences in Vietnam. Dr. Tran continued her academic journey by earning a PhD in Computer Science from Graz University of Technology (Austria). She has authored numerous papers/articles that have been published in prestigious venues such as ACM TiiS, JiiS (Springer), ACM RecSys, ACM UMAP, ACM IUI, AAAI, ECAI, ICSE, and others. Her research interests include recommender systems, human decision making, human computer interaction, configuration systems, and other AI-related topics. Dr. Tran has also actively contributed to the academic community by serving as a Peer Reviewer and Program Committee member for esteemed journals and conferences, such as the Journal of Intelligent Information Systems, RecSys, and UMAP. Currently, Dr. Tran's research topics focus on integrating human factors and psychological aspects in explaining recommendations, an emerging topic that is crucial for enhancing user satisfaction and overall experiences.

Alexander Felfernig is a full professor at the Graz University of Technology (Austria) since March 2009 and received his PhD in Computer Science from the University of Klagenfurt. He directs the Applied Software Engineering & Artificial Intelligence research group (ASE). His research interests include configuration systems, recommender systems, model-based diagnosis, software requirements engineering, different aspects of human decision making, and knowledge acquisition methods. He has published numerous papers in renowned international conferences and journals (e.g., IJCAI, AAAI, ECAI, ACM Recommender Systems, ACM Intelligent User Interfaces, AI Magazine, Artificial Intelligence, IEEE Transactions on Engineering Management, IEEE Intelligent Systems, Journal of Electronic Commerce) and is a co-author of the books on "Recommender Systems" published by Cambridge University Press, "Knowledge-based Configuration" published by Elsevier/Morgan Kaufmann, and "Group Recommender Systems" published by Springer. He also acted as an organizer of international conferences and workshops such as the ACM Conference on Recommender Systems, the International Symposium on Methodologies for Intelligent Systems, the International Workshop on Configuration, and the ACM Systems and Software Product Line Conference. He is a member of the Editorial Board of Applied Intelligence and the Journal of Intelligent Information Systems.

Viet-Man Le studied Computer Science at the Institute for Informatics in French-speaking areas (IFI), Vietnam, and graduated in 2011 as MSc with double diplomas from the University of La Rochelle, France and Hanoi University of Science and Technology, Vietnam. During his study at IFI, he gained a wide range of expertise in Machine Learning, Content-based Information Retrieval, and Information Visualization. In his Master's thesis, he presented an image browser using Self-Organizing Maps for visualizing images in which similar images are placed close together. He worked as a lecturer at the University of Economics, Hue University, Vietnam, from 2004 to 2019. At the moment, he is a Ph.D. student and works as a university assistant in the Applied Artificial Intelligence research group. His current research focuses on Configuration Systems, Recommender Systems, and Machine Learning.